OPTIMUM SOCIO-ENVIRONMENTAL FLOWS APPROACH FOR RESERVOIR OPERATION STRATEGY USING MANY-OBJECTIVES EVOLUTIONARY OPTIMIZATION ALGORITHM

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Abstract

Water resource system complexity, high-dimension modelling difficulty and computational efficiency challenges often limit decision makers' strategies to combine environmental flow objectives (e.g. water quality, ecosystem) with social flow objectives (e.g. hydropower, water supply and agriculture). Hence, a novel Optimum Social-Environmental Flows (OSEF) with Auto-Adaptive Constraints (AAC) approach introduced as a river basin management decision support tool. The OSEF-AAC approach integrates Socio-Environmental (SE) objectives with convergence booster support to soften any computational challenges. Nine SE objectives and 396 decision variables modelled for Iraq's Diyala river basin. The approach's effectiveness evaluated using two non-environmental models and two inflows' scenarios. The advantage of OSEF-AAC approved, and other decision support alternatives highlighted that could enhance river basin SE sectors' revenues, as river basin economic benefits will improve as well. However, advanced land use and water exploitation policy would need adoption to secure the basin's SE sectors.

Keywords: Environmental flows regime, Water resources management, Borg MOEA, ε-DSEA, auto-adaptive constraints, Diyala River basin

1 INTRODUCTION

The limits of water resources often lead to building dams in arid-environments to fulfil social and environmental demands such as flood wave absorption, water supply, agriculture projects, producing hydropower, tourist attraction, and other recreational purposes. These structures and their catchments need a robust management plan to handle their complexity in terms of: non-linearity, dynamic characteristics, conflicting objectives, multimodal, etc. (Haimes and Hall, 1977 in Reed et al., 2013).

In the last few decades optimization algorithms developed and carried out in different scientific and engineering fields to solve complex problems (Coello et al., 2007); these problems include water resources management (Maier et al., 2014). Multiple optimization methods used in reservoir system operation including linear and non-linear programing, dynamic programing and evolutionary algorithms (Ahmad et al., 2014; Rani and Moreira, 2010). Evolutionary algorithms (EA) widely employed to tackle the intricacies of reservoir systems, inspired from evolution of genes (Nicklow et al., 2010; Back et al., 2000). Studies involving multi-objective reservoir operation optimization using evolutionary algorithm summarized in Table 1. Only three of the twenty-two studies consider more than five objectives in reservoir operation strategy (multiple publications used in the same case study considered as one study). Besides, some studies merge objectives to simplify the multiple dam system problems, and hydropower generation and water supply (for domestic and irrigation) were the dominant objectives adopted in these studies.

Environmental objectives seldom adopted in reservoir management, in a recent review of studies between 1980 and 2015 by Horne et al., (2016) found only 42 studies adopt environmental releases in reservoir management as decision variables.

Recently Horne et al., (2017) presented conditional probability networks (CPNs) approaches combined with Mixed Integer Programing (MIP) optimizer for environmental flow regimes. Poff et al., (2016) propose a framework approach for eco-engineering decision scaling using performance indices, and Acreman et al., (2014) show that environmental flows need a "designer" approach for considering ecosystem objectives in water control infrastructure, rather than a "natural" approach.

Older studies do consider social objectives (hydropower, water supply, and flood protection) in their optimization models for reservoir operation strategy, and more recent studies consider environmental flow regimes. We propose to adopt a more holistic approach, where environmental flows from reservoir combined with the social water needs to improve economic revenues reliant on the river basin system.

Water resources management models provide information to the decision makers, rather than the decision itself (Loucks, 2012). There are pre and post-optimization implementation approaches for incorporating decision maker criteria within a multi-aspects problems (Maier et al., 2014; Coello et al., 2007). One of the pre-criteria approach drawbacks is the dissatisfaction (or lack of trust) of decision makers toward model results that emerged depending on their criteria set, and they may change these criteria to produce new results (Loucks, 2012). Hence the model needs to be re-executed until they get satisfaction. The second approach is computationally challenging and has potential difficulties to find the Pareto-front for optimum solutions set, which recently tackles by using multi-objective (or many-objective for more than three objectives) optimization algorithms (Maier et al., 2014).

These holistic challenges motivate development of a novel approach to produce optimum river basin management strategies that combines both social and environmental objectives. Many-objective evolutionary optimization algorithm adopted to conceptualise and analyse the multi-sector problem. Also, an auto-adaptive constraints approach used to overcome system complexity and boost algorithm convergence. The approach effectiveness evaluated using challenging water resources problem in a semi-arid region in Middle East. The approach achievement and robustness supported by two evolutionary algorithms (Maier et al., 2014): the state-of-the-art Borg MOEA (Hadka and Reed, 2013) and the new ε-DSEA (Al-Jawad et al., 2018b). The findings expected to improve the river basin system potential social and environmental sectors economic revenues. Also, the optimum water management strategy "trade-off" will provide the decision makers with a flexible flow regime management consistent with different time-scales for real-world IWRM.

2 METHODS AND TOOLS

2.1 Identification of OSEF-AAC Approach

This study presents the Optimum Socio-Environmental Flows (OSEF) approach which combines all social and environmental sectors (or objectives) together in one model using a many-objectives optimization algorithm approach.

Many-objectives model can solve more than three objectives problems (Maier et al., 2014; Li et al., 2015); however, the complexity increases exponentially when involving more objectives, which leads to challenges in computational efficiency (Lokman and Köksalan, 2013; Maier et al., 2014). Nevertheless, involving more objectives has minor or similar impact on the computational complexity of MOEAs' algorithms, since it's a function of; population size, number of objectives and number of generations (Curry and Dagli, 2014). The later study ended that involving more objectives to an optimization problem will have minor or similar computational complexity impact. This based on comparing two versions of MOEAs for multi and many-objectives optimization algorithms; NSGA-II (Deb et al., 2002) and NSGA-III (Deb and Jain, 2013); SPEA (Zitzler et al., 2002) and FD-SPEA2 (He et al., 2014). Also, they refer to the length of chromosome (number of decision variables) as a key-factor affecting on the computational complexity. Maier et al., (2014) explore computational efficiency challenges in water resources management models and the available methods to handle them, over the use of surrogate model (SM) or parallel computing. The SM approaches used to reduce the difficulties (or the dimensions) and the authors reviewed several studies carrying out the SM model, noting "*SMs are only an approximation and therefore subject to errors*" (Maier et al., 2014). While the parallel computing is not commonly available and highly expensive, another challenging are the barriers (or constraints) that real-world water resources management problems have which limit the model feasible solutions region. For examples dam releases restricted to the spillway gates' maximum discharge capacity, and power generation limited to the maximum power plant turbine flows. Hence, constraints should assign for unconstrained optimization algorithms like evolutionary algorithms (Deb, 2001; Abraham et al., 2005).

Developing a penalty function formula is a type of constraints approach paradigm (Coello Coello, 2002; Simon, 2013) to represent decision makers policy or criteria (Maier et al., 2014) and to exaggerate the unfeasible solution to guide algorithm exploration towards feasible solutions. However these functions should carefully develop and test for each problem to avoid premature or delay of algorithm convergence towards optimum solutions (Deb and Datta, 2013). Hence, the new Auto-Adaptive Constraints (AAC) method developed to overcome such challenges. The AAC developed after intensive practical diagnosis and assessment of evolutionary algorithm behaviour on real-world many-objectives problem with large number of decision variables. The initial decision variables population random seeding produces feasible and unfeasible candidates in the decision variables design space. Then these candidates subjected to mutation and crossover evolution to produce new generations until evaluation ends (Deb, 2001; Abraham et al., 2005), which is sensitive to objective achievement to produce non-dominated solutions. Therefore, the initial evaluation stages produce large penalized values due to numerous decision variables' violations which restrains the convergence or may cause stagnation in local optima (Deb and Datta, 2013). To overcome this problem, the AAC approach release the chain of constraints at large values of violation gradually, then re-enforce it at small violations, as decision variables approach feasible region. The method based on a dynamic like combining the penalty formula with model violations. Figure 1 shows the diagram of OSEF-AAC and AAC details approaches.

2.2 Identification of Many-Objectives Optimization Algorithms

Hadka and Reed (2013) present the state-of-the-art Borg MOEA for many-objectives optimization problem with auto-adaptive six recombination operators, ε-box techniques for dominance sorting, injection technique (Kollat and Reed, 2006) to avoid stagnation, and an archive for dominance solutions sorting. Comparative assessment studies of Borg MOEA achieved by Hadka and Reed (2012), Hadka et al. (2012), Reed et al., (2013), Woodruff et al. (2015), Zatarain Salazar et al., (2016), and (Yan et al., 2017) on various problems with competitive evolutionary algorithms (like NSGA-II, AMALGAM, ε-MOEA, SPEA2, .. etc.) shows outperformance of Borg MOEA. Recently, Al-jawad and Tanyimboh (2017) assessed Borg MOEA to solve real-world reservoir operation; results show that Borg MOEA improves the solution significantly.

New methods proposed by in developing ε-DSEA to increase the diversity and improve model convergence. ε-DSEA has self-adaptive operators' parameters control technique for auto-parameter-tuning and random parameters resetting to avoid stagnation. The ε-DSEA intensively tested on five benchmarks functions with up to 8-objectives, five objectives real-world reservoir operation problem, and a real-world groundwater long-term management (Al-Jawad and Tanyimboh, 2018; Al-Jawad et al., 2018). The results showed that ε-DSEA outperformed Borg MOEA in almost all adopted cases.

3 CASE STUDY DESCRIPTION

3.1 Regional Identification

The Himren dam system in Iraq selected as a challenging water resources problem, located in the semi-arid region in the Middle East, which has many social and environmental management problems. It is a rock fill multi-purpose dam located in the Diyala governorate of Iraq at 34º 06’ 45” N – 44º 58’ 11” E, 120 km in the north-east from Baghdad city (Figure 2a).

The dam built for hydropower production, flood control, agriculture and reregulate river flows for downstream water exploitation. Table A2 and A3 in the *supplementary data* presents Himren dam characteristics details, and the average monthly meteorological data, precipitation, evaporation, river losses, and irrigation projects demands for the dam system, respectively. The Diyala river basin is facing crisis and deterioration in the sustainability of its water resources and environments. Details identification of the problem illustrate in section 2 in the *supplementary data*.

3.2 Identification of Reservoir Management Objectives (OSEF-AAC approach)

In general, each river basin has its own operation objectives and constraints, hence mathematical models developed for the adopted case study for OSEF-AAC approach implementation. Water resources management decisions may relate to a range of spatial and temporal scales, from sub-daily to multi-year and a single location to the river basin, respectively. However monthly rather weekly values considered in the model as the focus of the research is to support developing an efficient seasonal managing policy, rather than daily operational control (Horne et al., 2016). Figure 2b shows the proposed nine objectives of Himren dam physical model. The river basin management system is classified into two main groups, social and environmental.

3.2.1 Social Sector Objectives

This sector includes objectives addressing water demands, storage support, flood risk management, and power generation. To fulfil downstream water demands for domestic, industrial, and irrigation projects at time *t* (DD_t^H), the relevant reservoir releases (R_t^H) should manage to follow these demands over the time operation *T*, which can formulate as:

$$min\, f_{demandsH} = \sum_{t=1}^{T} \left(\frac{R_t^H - DD_t^H}{DD_{max}^H} \right)^2 + C_P \quad , t=1, 2,..T \tag{1}$$

where DD_{max}^H is the maximum water demands, and C_P is the penalty value includes all the violations of the model, which could express as:

$$C_P = \sum_{i=1}^{PN} C_i^e \quad , i=1, 2,..PN \tag{2}$$

where *PN* is the number of penalty functions, C_i is the penalty value for the (i^{th}) penalty function, and *e* is any positive integer number. More details of C_i presents in equations 19 and 20 below.

In arid environments one of the main reasons for a dam is to support reservoir storage during rainy seasons (T_W), usually in winter, to fulfil water demands in hotter / dryer seasons. Hence the reservoir storage at time *t* (S_t^H) should increase to the maximum reservoir storage (S_{max}^H). Therefore, the second social objective can express as:

$$min\, f_{winterH} = \sum_{t=1}^{Tw} \left(\frac{S_{max}^H - S_t^H}{S_{max}^H} \right)^2 + C_P \quad , t=1, 2,..\, T_W \tag{3}$$

The reservoir water storage budget is affected by the quantity of reservoir inflows (I_t^H), the reservoir releases (R_t^H), reservoir lake evaporation (E_t^H), direct rainfall (P_t^H), reservoir seepage losses (SE_t^H), and reservoir groundwater recharge (GR_t^H). Hence, reservoir storage at time *t*+1 (S_{t+1}^H) could express as:

$$S_{t+1}^H = S_t^H + I_t^H - R_t^H - E_t^H + P_t^H - SE_t^H + GR_t^H \quad , t=1, 2,.. T \tag{4}$$

Reservoir area-storage and head-storage relation presented in the section 3 in the *supplementary data*. Flood risk management strategy should consider in the operation policy to reduce inundation hazards, and can manage by reducing reservoir storage during the summer season (T_S) before the next rainy season. However, the minimum producing power (S_{minp}^H) need to preserve during this period. Hence the third social objective can formulate as:

$$min\, f_{summerH} = \sum_{t=1}^{Ts} \left(\frac{S_t^H - S_{minp}^H}{S_{max}^H} \right)^2 + C_P \quad , t=1, 2, .. T_S \tag{5}$$

Producing power is one of the main economic purposes considered in dam operational design. Therefore, the fourth social objective is to maximize the power generation at time *t* (Pw_t^H) towards the maximum power plant capacity (Pw_{max}^H) over the operation time T to improve project revenues using the following formula:

$$min\, f_{powerH} = \sum_{t=1}^{T} \left(\frac{Pw_{max}^H - Pw_t^H}{Pw_{max}^H} \right)^2 + C_P \quad , t=1, 2,..T \tag{6}$$

The general hydropower generation formula is as follows:

$$Pw_t^H = \eta_e^H . \gamma_w . Q_t^{tuH} . H_t^{nH} \tag{7}$$

where η_e^H is power plant efficiency, γ_w is water specific weight, Q_t^{tuH} is the turbine discharge, and H_t^{nH} is the net head in the reservoir measured between reservoir water surface level and the tail water level after the dam structure (after the hydropower turbine structure).

3.2.2 Environmental Sector Objectives

The objectives of this sector can express as: controlling river discharges, river water quality, downstream water quality, and river morphology. The harmony in river flows is important for controlling river morphology, navigation and tourism in the region. Since the Diyala barrage on dam downstream controls reservoir releases, extra control should consider within the management model. A new Barrage operation policy proposed to improve river environment, which its details are in section 4 in the *supplementary data*. Hence the second environmental objective is to minimize the river discharge differences at time t (Q_t^r) and t+1 (Q_{t+1}^r) with respect to the maximum river discharge (Q_{max}^r) for the entire periods time T. The following formula proposed:

$$min\, f_{riverB} = \sum_{t=1}^{T} \left(\frac{Q_t^r - Q_{t+1}^r}{Q_{max}^r} \right)^2 + C_P \quad , t = 1, 2,..T \tag{8}$$

The river water quality is important for ecosystem and anthropogenic needs; therefore, reservoir releases management should consider this issue. Where a pollutant source discharges to the river, the final concentration of total dissolved solids after the source point at time t (TDS_t^{r2}) depend on the mixed concentrations of pollutant source and the river (TDS_t^{PS}, TDS_t^{r1}) coupled with their discharges (Q_t^{PS}, Q_t^{r1}), respectively. Hence, the final concentration can calculate using mass solute balance equation:

$$TDS_t^{r2} = \frac{TDS_t^{r1} \times Q_t^{r1} + TDS_t^{PS} \times Q_t^{PS}}{Q_t^{r1} + Q_t^{PS}} \quad , t = 1, 2,..T \tag{9}$$

Thus, the second environmental objective is to minimize river pollutant after the pollutant source over the operation time T, which can express as:

$$min\, f_{TDS-DY} = \sum_{t=1}^{T} \left(\frac{TDS_t^{r2}}{TDS_t^{PS}} \right)^2 + C_P \quad , t = 1, 2,..T \tag{10}$$

Consistency, since the Diyala River is merging with Tigris River downstream, the mixing water should also monitor. So, the mix concentration after the confluence (TDS_t^R) depends on both rivers quality and quantity $TDS_t^{r2}, Q_t^{r2}, TDS_t^{r3}, Q_t^{r3}$, respectively, which could express as:

$$TDS_t^R = \frac{TDS_t^{r2} \times Q_t^{r2} + TDS_t^{r3} \times Q_t^{r3}}{Q_t^{r2} + Q_t^{r3}} \qquad , t = 1, 2, .. T \tag{11}$$

The third environmental objective is to minimize the final mixed concentration in Tigris river after the confluence with Diyala river about the maximum allowable concentration of (TDS_{max}) over the operation period T, which can formulate as:

$$min\, f_{TDS-TR} = \sum_{t=1}^{T} \left(\frac{TDS_t^R}{TDS_{max}} \right)^2 + C_P \qquad , t = 1, 2, .. T \tag{12}$$

River morphology is another environmental aspect considered through degradation and aggregation in the riverbed at section i and time t according to the Schoklisch formula (1934) (Yang 1996 in Ali 2016) and it depends on river discharge per unit width ($q_{i,t}^r$), critical discharge per unit width ($q_{i,t}^c$), energy gradient of water ($HG_{i,t}$), and soil particle diameter (d_s). Hence, the riverbed sediment loads discharge ($BD_{i,t}$) per unit width is:

$$BD_{i,t} = \frac{7000\, HG_{i,t}^{3/2}}{\sqrt{d_s}} . \left(q_{i,t}^r - q_{i,t}^c \right) \qquad , t = 1, 2, .. T, i = 1, 2, .. NS \tag{13}$$

where NS is the number of considered sections along the river

$$q_{i,t}^c = \frac{1.944 \times 10^{-5} . d_s}{HG_{i,t}^{4/3}} \tag{14}$$

The energy gradient at section i and time t could be calculated using Manning's formula, which depends on Manning's roughness coefficient (n), river discharge (Q_t^r), effective flow area ($A_{i,t}$), and hydraulic radius ($HR_{i,t}$) of the river section

$$HG_{i,t} = \frac{n^2 (Q_t^r)^2}{A_{i,t}^2 HR_{i,t}^{4/3}} \qquad , t = 1, 2, .. T, i = 1, 2, .. NS \tag{15}$$

Carriaga and Mays (1995) and Nicklow and Mays (2001) proposed sediment routing formula in the river to calculate the bed level change at section *i* and time *t* ($BL_{i,t}$), and time *t*+1 ($BL_{i,t+1}$), respectively. Their formula depends on the difference between bed load discharge at section *i*-1 and *i*+1 ($BD_{i-1,t}$, $BD_{i+1,t}$), specific density of water-soil mixture (γ_m), river bed width (W_i), and the length between the considered section and the upstream section ($L_{u,t}$) and downstream section ($L_{d,t}$). Hence, the aggregation and degradation at *i* section in any time difference ΔT along riverbed could be calculated as follows:

$$BL_{i,t+1} = BL_{i,t} - \frac{\Delta T_t}{0.5\gamma_m W_i} \frac{\left(BD_{i-1,t} - BD_{i+1,t}\right)}{\left(L_{u,t} + L_{d,t}\right)} \qquad , t = 1, 2, .. T, i = 1, 2, .. NS \tag{16}$$

In order to minimize the changes in river bed levels over the operation time *T*, the following formula proposed:

$$min\, f_{DY-BCH} = \sum_{i=1}^{NS} \left(\frac{BL_{i,t=0} - BL_{i,t=T}}{\Delta BL_{max}} \right)^2 + C_P \qquad , t = 1, 2, .. T \tag{17}$$

where ΔBL_{max} is the maximum allowable river bed level changes

3.2.3 Model Violation Objective

The final objective function is to minimize the penalty function value (C_P) to force the optimization algorithm to search in the feasible space of the problem, as follows:

$$min\, f_{MD} = C_P \tag{18}$$

When model system boundaries violated over the evaluation, the following formula proposed for the entire model violation (Chang et al., 2010; Al-jawad and Tanyimboh, 2017):

$$C_i = A_i . \sum_{j=1}^{T} g_j \, ; \;\; A_i \geq 1 \tag{19}$$

where, (g_j) is the penalty function of (j^{th}) constraint. Details of the constraints formulas (g_j) for the reservoir operation management are as follows:

- Equations 20 to 23 are for reservoir minimum, maximum, sustainable storage control
- Equations 24 to 26 are for hydropower generation and penstock discharge limits
- Equations 27 and 28 are for controlling reservoir releases
- Equations 29 and 30 are for minimum and maximum river discharge
- Equations 31 and 32 are for river water quality control
- Equations 33 to 35 are for controlling riverbed changes, respectively

$$g_1 = \sum_{t=1}^{T} Max[0, (S_t - S_{min})] \tag{20}$$

$$g_2 = \sum_{t=1}^{T} Max[0, (S_{max} - S_t)] \tag{21}$$

$$g_3 = \sum_{t=1}^{T} Max[0, \mu_1(S_t)] \tag{22}$$

$$\mu_1(S_t) = \left\{ \begin{matrix} 0 \\ 0.5 \times (1 - cos\left(\frac{(S_t - S_{minp})}{(0.9 \times S_{T+1} - S_{minp})}\right) \\ 1.0 \end{matrix} \middle| \begin{matrix} S_t \geq 0.9 \times S_{T+1} \\ S_{minp} < S_t < 0.9 \times S_{T+1} \\ S_t < S_{minp} \end{matrix} \right\} \tag{23}$$

$$g_4 = \sum_{t=1}^{T} \left\{ Max[0,1] \middle| \begin{matrix} Pw_t < Pw_{min} \\ Pw_t > Pw_{max} \end{matrix} \right\} \tag{24}$$

$$g_5 = \sum_{t=1}^{T} Max[0, (Q_t^{tu} - Q_{min}^{tu})] \tag{25}$$

$$g_6 = \sum_{t=1}^{T} Max[0, (Q_{max}^{tu} - Q_t^{tu})] \tag{26}$$

$$g_7 = \sum_{t=1}^{T} Max[0, (R_t - R_{min})] \tag{27}$$

$$g_8 = \sum_{t=1}^{T} Max[0, (R_{max} - R_t)] \tag{28}$$

$$g_9 = \sum_{t=1}^{T} Max[0, (Q_t^r - Q_{min}^r)] \tag{29}$$

$$g_{10} = \sum_{t=1}^{T} Max[0, (Q_{max}^r - Q_t^r)] \tag{30}$$

$$g_{11} = \sum_{t=1}^{T} Max[0, \mu_2(TDS_t^R)] \tag{31}$$

$$\mu_2(TDS_t^R) = \left\{ \begin{array}{c} 0 \\ 0.5 \times (1 - cos\left(\frac{(TDS_t^{r3} - TDS^{max1})}{(TDS^{max2} - TDS^{max1})}\right) \\ 1.0 \end{array} \middle| \begin{array}{c} TDS_t^R \leq TDS^{max1} \\ TDS^{max1} < TDS_t^R < TDS^{max2} \\ TDS_t^R \geq TDS^{max2} \end{array} \right\} \tag{32}$$

$$g_{12} = \sum_{t=1}^{T} Max[0, \mu_3(\Delta BL_i)] \tag{33}$$

$$\mu_3(\Delta BL_i) = \left\{ \begin{array}{c} 0 \\ 0.5 \times (1 - cos\left(\frac{(\Delta BL_i - BL_{max1})}{(BL_{max2} - BL_{max1})}\right) \\ 1.0 \end{array} \middle| \begin{array}{c} \Delta BL_i \leq BL_{max1} \\ BL_{max1} < \Delta BL_i < BL_{max2} \\ \Delta BL_i \geq BL_{max2} \end{array} \right\} \tag{34}$$

$$\Delta BL_i = \left| BL_{i,t=1} - BL_{i,t=T} \right| \tag{35}$$

In this research, the AAC approach adopted for the factor (A_i) for the environmental constraints. In reservoir releases management, these constraints relevant with ecosystem requirement such as river flow, river water quality, sediment transport, navigation …etc. The factor (A_i) first set for an initial value, then these values dynamically adapted with the corresponding penalty function (C_i) using the following formula, which developed empirically:

$$A_i = \begin{Bmatrix} A_i - \left(\frac{1}{\sqrt{C_i}}\right) & if\ C_i \geq 1.0 \\ A_i + 1.0 & otherwise \end{Bmatrix}, A_i \geq 1.0 \tag{20}$$

Two scenarios adopted using a historical data from 1981 to 2012. Scenario-1 projects of the historical data for the next future inflows. Scenario-2 reflects the predicted climate changes impacts on reservoir inflows for the next thirty-three years. Details of proposed scenarios presented in section 5 in the *supplementary data*.

Table 2 shows operation and environment parameters of reservoir system. The operational parameters include the physical limits of reservoir storage, releases, turbine and river discharges, while the environmental parameters include water quality limits, river morphology, and storage sustainability.

3.3 Computational Model Implementation

Using in the programming language C, a model developed to conceptualize all the objective functions and the related constraints. For completeness, both the Borg MOEA and the ε-DSEA algorithms replicated 20 times for each scenario, with the number of function evaluations equal to 500,000 and epsilon (ε) (ε is the resolution of the objective search space) equal to 0.5 for the nine objectives for both scenarios. The number of decision variables, 396, equals the number of monthly releases over the thirty-three years' data period. Also, other reservoir parameters system including storage, surface area, water level, and power producing calculated by the model; hence the model solved 3564 variables in each run. The overall function evaluation total is 40 million, with total processing time about 80 hours CPU time. The optimization running made using PC desktop (Core i7-6700 CPU @ 3.4 GHz, 16 GB RAM) with Ubuntu 16.04 OS. The parameters used for both algorithms shown in Table A3 in the *supplementary data*.

In the current study, a value of $A = 10^4$ selected for the dam physical model's constraints to exploit all feasible solutions and avoid rendering infeasible solutions at the constraints threshold, especially those with small violation values. While $A_i = 10^2$ (Al-Jawad and Tanyimboh, 2017) selected as starting value for the environmental constraints, as described in section 3.2.3.

4 RESULTS

4.1 Optimum Trade-off Achievement

The MOEAs' effectiveness commonly measured using metrics like the hypervolume metric (Zitzler, 1999) which evaluate the non-dominated solutions' hypervolume, and generational distance metric (Van Veldhuizen and Lamont, 1998) which measure the average distance between the dominance solutions and the closer Pareto-front set. However, these metrics (and others) may provide misguiding results and most of their design principles depends on the true Pareto-front, which is unknown in real-world water resources management problems (Maier et al., 2014). Accordingly, qualitative and quantitative parameters adopted for achievement assessment. The optimization results shown in Figure 3, here the ε-DSEA outperforms Borg MOEA in both scenarios for the near median Pareto-front values achieved from the 20 runs for each scenario, since the range of objectives functions values achieved by ε-DSEA are lower than those in Borg MOEA.

The mean numbers of dominance solutions achieved by ε-DSEA and Borg MOEA in both scenarios were about 721, 406; 771, 368; and the median were 372, 286; 815, 273, respectively. While, the gross number of dominance solutions achieved by both algorithms for the adopted scenarios were 14410, 8118; 15415, 7363, respectively, hence the ε-DSEA has advance diversity than Borg MOEA. Convergence speed is another parameter chosen for performance assessment, which represents algorithm's efficiency. Figure 4 illustrates convergence development of model objectives functions over the evaluation process for both algorithms and scenarios. It is clearly that ε-DSEA converge faster than Borg MOEA in both scenarios. Hence the ε-DSEA's solutions adopted for interpretation of the reservoir operation management. Detail competitive analysis results for both algorithms presented in section 8 in the *supplementary data*.

Figure 3 also shows that the total model violation function is greater than one ($f_{MD} > 1.0$) in all cases, which refers to unfeasible solutions achievement in the objective search space. However, these solutions located in both the feasible and unfeasible regions in the decision variables search space. Table 3 illustrates the summary of Himren dam system parameters achieved by ε-DSEA for both scenarios. The reservoir releases, storage, water level, surface area and hydropower generation did not violate its barriers; hence their objectives attainment emerged from feasible decision variables. Also, the Diyala River discharges preserved below river's maximum capacity, as they controlled by Himren dam and Diyala Barrage. However, Diyala River morphology and Tigris River water quality had violated slightly about their preferable limits (riverbed changes ≤ 2.0, TDS ≤ 600 mg/l) specified by NCWRM (the decision makers). This refers to the reservoir releases inertia to satisfy these limits over the operation periods, hence some decision variables located in the unfeasible region of the decision variables space.

4.2 Auto-Adaptive Constraints' Approach Achievement

The new AAC approach succeeds to guide the optimization algorithm towards possible optimum solutions. Figure 5 shows the values of penalty factors (A_i) with the corresponding penalty function value (C_i) over the evaluation process for both scenarios.

This Figure illustrates how A_i's values dynamically changed with the corresponding penalty function value (C_i) when $C_i \geq 1.0$. However, the riverbed changes penalty factor A_4

remains at minimum value ($A_4 = 1.0$) in both scenarios, since its penalty value C_4 is greater than one over the entire evaluation process. The riverbed changes including aggregation and degradation, mainly affected by water flow velocity and riverbed sediment grain size. The flow velocity is directly proportion with reservoir releases; hence inconsistent releases may cause changes in riverbed morphology, depending on bed sediment grain sizes. Here, because of lack data, the adopted mathematical model of riverbed changes simplified using averaging riverbed width, and assuming water energy gradient equal to the riverbed slop. Therefore, detail cross-sections, bed sediment grain size, and other parameters needed to improve the control of river morphology changes.

4.3 Sensitivity of Computational Parameters

Based on the use of a feedback loop from the dominance archive, pre-execution tuning (or setting) of the operators' parameters is not required in ε-DSEA. The novel self-tuning technique is sensitive to the problem environment over the different stages of optimization progress. The parameters' sensitivity of operators SBX, PCX, and SPX during problem evaluation of 20 runs for both scenarios are shown in Figure 6. Obviously, at each random seeding repetition and at each scenario, the operators' parameters varied during problem evaluation progress phase, based on operators' efficiency to produce dominance solutions. The SBX distribution index (η) often adopted values larger than 50 in scenario-1 after 25×10^4 of function evaluation. In scenario-2, the parameter adopted different values within the specified domain (0 to 100) over optimization progress. The PCX distribution variation parameters ($\sigma_\eta, \sigma_\zeta$) ranged between 0.1 and 0.2 in scenario-1. In scenario-2, they changed from 0.1 to 0.25 in the first quarter stage of evaluation, then from 0.1 to 0.15. The expansion rate parameter (λ) of PCX has consistent behaviour as PCX, with a range of 2.5 to 3.0 in general.

The sensitivity of parameters' self-tuning to optimization results showed in Figure 7. Clearly, ε-DSEA preserve consistent optimum results in all execution repetitions especially in scenario-2, except few runs. Conversely, Borg MOEA shows unreliable achievement in both scenarios, especially in scenario-2, by producing inconsistent results over the considered repetitions, based on its parameters' default values. Thus, ε-DSEA is more reliable than Borg MOEA.

4.4 Reservoir Operation Strategy

Although the decision of adopting any optimum solution depends on the decision makers' decision, we will propose a solution emerged from the best achievement of each objective, which could be beneficial for the decision makers to consider. The corresponding reservoir releases for optimum solutions are presented in Figure 8, (a) and (b) for both scenarios respectively. It clearly that these results are consistent, hence an average values for reservoir releases was generated, as shown in Figure 8 (c) and (d) for both scenarios, respectively. The details of other corresponding variables of the system like: reservoir storage, surface area, hydropower generation, etc., for both scenarios are presented in section 7 in the *supplementary data*.

The summary of the outcomes is illustrated in Table 4; from this data there emerges an optimum socio-environmental flows regime for long-term reservoir system management strategy that could be adopted by the decision makers. Furthermore, improvements were achieved in different sectors in the river basin (e.g. hydropower generation, crop production, water industry, etc.). The mean hydropower generated in scenario-1 was about 26 MW over three decades with standard deviation about 14 MW, while in scenario-2, is about 21 MW and 12 MW, respectively. The mean agriculture water delivery for both scenarios were maintained between about 157 MCM and 137 MCM, respectively. However, these values show deficit in water delivery when compared with the actual design demands. Hence, the government should adopt future policy to assess other alternatives to reduce the water deficit, such as reducing crop patterns, changing crops types, using groundwater, changing irrigation method (e.g. sprinkles, drips), developing water conveyance infrastructure, etc.

Furthermore, the reservoir storage was also maintained with its limits with a mean value about 1.3×10^9 m^3/month for both scenarios. This provides suitable space when compared with the normal storage of 2.4×10^9 m^3/month, to absorb flood waves and reduce the possible flood risk impact on the community downstream the river. However, future government led policies should also consider flood alarm systems for advance flood control. Additionally, reservoir seepage losess and advanced data collection systems should be included in their policy for comprehensive water resources management.

With consistency, the proposed operation policy for the Diyala barrage maintains a minimum discharge about 30.8 MCM in both scenarios, which is equivalent to about 12 m^3/s; this is more than the minimum river discharge of 10 m^3/s. Also, the model predicts maintenance of the mean and median changes in river morphology less than one meter in both scenarios over the entire period, which mitigates the impact of load sediment transport on downstream projects. Sediment movement impacts navigation, water supply projects, and for river hydraulic infrastructures in the downstream, which raise maintenance costs to overcome these problems.

The impact of Diyala river environment improvement was also observed by maintaining Tigris water quality (TDS) less than 613 mg/l in both scenarios over the entire periods, predicted management would have a positive economic impact on the water supply projects, farming, and the industry in downstream cities and villages. However, river quality should be monitored in case of shortage in Tigris water resources to avoid any deterioration due to high TDS concentration in Diyala river discharges.

However, the current model's temporal (regional extension) and special scale (No. of decision variables) is relevant to the adopted case study, which can be extended for other problems for future works.

4.5 Effectiveness of OSEF-AAC approach

Two extra optimization management models (M2, M3) proposed to identify the effectiveness of the current model (M1) using scenario-1. Model M2 employs Equations 1, 6, and 18 of objective functions, and M3 Equations 1, 3, 5, 6, 8, and 18. The M1 achievement considered as a datum, thus the differences of M2-M1 (Δ_{3-9}), and M3-M1 (Δ_{6-9}) were developed, as shown in Figure 9. The total gross differences (Δ_{Gross}) of; reservoir storage, power generation, releases; farms' delivered water farms; and river discharge showed by Figure 9a. Extra reservoir storage and river discharge achieved via M2 model (89.6×10^9 m^3, 4.7×10^9 m^3), however releases, hydropower and farms' delivery water were less (-2.35×10^9 m^3, -0.76 GW, -7.1×10^9 m^3), in comparison with M1. For Δ_{6-9}, the storage, power generation, and farms' water delivery were less (-35.3×10^9 m^3, -0.25 GW, -0.85×10^9 m^3), while slightly higher values achieved for releases and River discharge by M3.

Figures 9b and 9c show the contrast of the mean and median TDS concentration of Diyala and Tigris Rivers achieved by the M2 and M3 models, with M1 model as a datum. Clearly, M2 achieved higher TDS concentration than M3 before and after WWTP at Diyala River for both mean and median values. For M2, the Δ_{Mean} and Δ_{Median} were 202, 286 mg/l; 600, 905 mg/l at before and after WWTP, and for M3 were 72, 100 mg/l; 151, 251 mg/l, respectively. Notably, the proposed model (M1) with nine objective functions achieved better socio-environmental flow regime than M2 and M3 models with three and six objective functions, respectively.

5 DISCUSSION

In this research, a reservoir operation strategy produced using novel socio-environmental flow regime approach. Nine objective functions, twelve constraints, and two inflows' scenarios employed relevant to Himren dam system in Iraq. Conflicts between model objectives are obvious in both scenarios (Figure 3), except for f_{TDS-TR} and f_{DY-BCH} which have soft conflicts, since their relations are indirect. At Tigris and Diyala Rivers' junction, the quality of mixed water is sensitive to their relevant quality and quantity. While Diyala River morphology directly affected by the relevant discharge. The degree of mutual influence between power generation objective (f_{power}) and flow control objective (f_{riverB}) is medium since most of reservoir releases diverted to the agriculture projects by Diyala Barrage. Handling multiple conflicts objectives simultaneously produces a set of optimum solutions (Deb, 2001) (trade-off) adaptive with decision makers' criterion.

The novel penalized feedback formula succeeded to soften the computational complexity of many-objectives problem. The early convergence from infeasible to feasible region (Figure 4) supports improving search space's exploration and exploitation. The current formula may justify for other case studies.

The ε-DSEA robustness and reliability are obvious (Figures 3, 4, and 7) based on twenty executions, in comparison with Borg MOEA. The ε-DSEA self-tuning technique limits time-wasting of pre-execution tuning of crossover operators' parameters (Figure 6). In classical hybrid algorithms like Borg MOEA and AMALGAM (Vrugt and Robinson, 2007) that employ multiple crossover operators, the possible tuning combination trials are directly proportion with the number of operators' parameters. For example, Borg MOEA has six operators with nine parameters, thus 9! (362,880) tuning trials needed to explore their sensitivity of the results' optimality. Therefore, default values based on previous experimental studies adopted in such algorithms. But, this may leads a drawback in algorithm's optimality merit when solving problems that have different environments (Maier et al. 2014; Karafotias et al. 2015).

Usually the operation management priorities based on the stakeholders' demands. Here domestic demands are a key priority, and other objectives have secondary priorities. A maximum TDS of 600 mg/l (Alsaffar, 2017) recommended at the river, while a top of 620 mg/l preserved after Rivers' junctions over the considered period and scenarios, in contrast with recently recorded range of 600 to 1200 mg/l. Thus, the government needs to adopt advance treatment policy of Al-Rustumiya plant's discharges to improve downstream environments.

The previous argument shows the importance of understanding reservoir management priorities in developing system objectives functions and constraints to represent these priorities. Further, partial violated solutions in secondary priorities could adopt for reservoir operation strategy. The model results' reliability supported by Alsaffar, 2017, based on current operating management strategy, especially the median reservoir releases in scenario-2. Hence, the method of scenario-2 could adopt to represent climate change impact in other part of this region.

The prediction picture delivered to the decision makers displays the valuable of considering social and environmental objectives in the river basin over different scenarios. However, alternatives (scenarios), like out boarder upstream development projects impacts on downstream river basin system, could carry out for further insight approach assessment.

Combining environmental objectives succeed to improve water quality in downstream of Diyala River. Masking environmental objectives in models M2 and M3 produce higher pollutant's concentration at the river. However, including more objectives in M3 improve the mean and median water quality about 9%, and 26%, respectively. Notably, M2 and M3 models produce slightly higher river flow than M1, but M1 carried out better water quality. Thus, M1 model produces better operation strategy (or flow regime) than other models, since environmental aspects involved as objective functions.

The study results also show how the system is sensitive to the reservoir inflows, which affected by the releases from the upstream reservoir (Derbindikhan dam reservoir), out-of-border tributaries and upstream direct runoff and water exploitation. Hence, the Iraqi government should consider future policies to restrict unauthorized water use in upstream region. Also they should consider developing water sharing agreement with Iran to avoid future water crisis in the basin. Therefore, the river basin needs further future management development to involve the previous features (and others) for fully river basin management, which known as integrated water resources management (IWRM). Finally, this study's novel approach shows how environmental features could improve when they considered in the reservoir operation management, and how they will promote the potential economic benefits for the entire system.

The current approach could perform at any reservoir operation problem (i.e. combining social with environmental objectives using many-objective optimization algorithm). The proposed mathematical optimization model is relevant to the current case study and/or similar problems, and can adjust for other region to adapt with the physical models' operation objectives and constraints.

6 CONCLUSIONS

In this research a novel Optimum Social-Environmental Flows approach with Auto-Adaptive Constraints (OSEF-AAC) was developed to improve the river basin management strategy which combines all social and environmental objectives in the river basin. The research used a many-objectives evolutionary optimization algorithm to generate a trade-off to the decision makers. This approach was developed to fill the gap of combined environmental flow regimes in the reservoir operation strategy (Horne et al., 2016; Horne et al., 2017), and to overcome the complexity and computational challenges of such models (Maier et al., 2014).

The OSEF-AAC was evaluated and assessed using a challenging case study in the Middle East. The Himren dam at Diyala river basin was modelled using nine social and environmental objectives with 396 decision variables. The state-of-the-art Borg MOEA and the new ε-DSEA optimizers, two predicted inflows' scenarios, and two comparative non-environmental models were employed. The algorithms' computational analysis results show the ε-DSEA outperformed the Borg MOEA in almost all cases. The AAC approach succeed to overcome the complexity of the problem, boosting algorithm convergence toward possible optimum solutions and avoiding algorithm stagnation in local optima. The reliability of ε-DSEA techniques were also endorsed, hence its results were adopted. The OSEF-AAC effectiveness was evident, based on comparison with other proposed models.

The reservoir releases optimum trade-off emerged from the OSEF-AAC approach integrate all adopted social and environmental sectors in the river basin including hydropower generation, flood risk management, river quality, river sediment transport, reservoir storage control, agriculture water delivery, discharge regulation, and downstream water quality. More objectives could be embedded to the approach for comprehensive flows regime (e.g. fisheries, navigation and tourism). The decision makers can adjust the trade-offs and adopt those that fit their criteria.

However, to fully develop the potential achievement of the OSEF-AAC approach, an average optimum solution was generated using optimum solution achieved by each objective. The results show improvement in reservoir system environments in all sectors, as follows:

- *Environmental Sectors:* The Diyala river water quality (TDS) was improved after a pollutant source from about 2600 mg/l to about 2400 mg/l, which leads to improve the downstream water quality mean value of TDS from about 750 mg/l to 570 mg/l for both scenarios. This will decrease water remediation cost in downstream region. Additionally, the mean and median river morphology changes were maintained within one meters for both scenarios over the considered period. Hence, positive impacts on the maintenance cost for water supply and hydraulic structures in the river were achieved.

- *Social Sector:* The power revenues were improved over continues hydropower generating for the next three decades under two scenarios. Future investment opportunities plans could be set from the mean values 26 MW and 21 MW obtained for both scenarios, respectively. Moreover, the storage control objectives were succeeded to preserve free mean reservoir storage about 1.0×10^9 m^3 for flood wave absorption, which mitigate the possible flood risk and reduce the cost of inundated indemnity for lands and properties. For crop production, the mean and median agriculture water deficit for both scenarios were maintained within the range of 18-28% and 30-35%, respectively, which robust crop investment revenues.

The adopted mathematical optimization model for the current case study considers only the common management objectives based on the available database. However, other issues like; water influent and affluent of Reservoir Lake, ecosystem and navigation objectives, etc. could be implemented for future works.

Finally, the OSEF-AAC approach can be adopted to solve any river basin management problems to generate optimum socio-environmental flows regime. These provide decision makers a trade-off for developing robust management strategy towards achieving better economic revenues for the water-energy-food nexus objectives of a river basin.

Recommendations for the decision makers to improve the lower Diyala river basin environment are presented in section 8 in the *supplementary data*.

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FIGURES

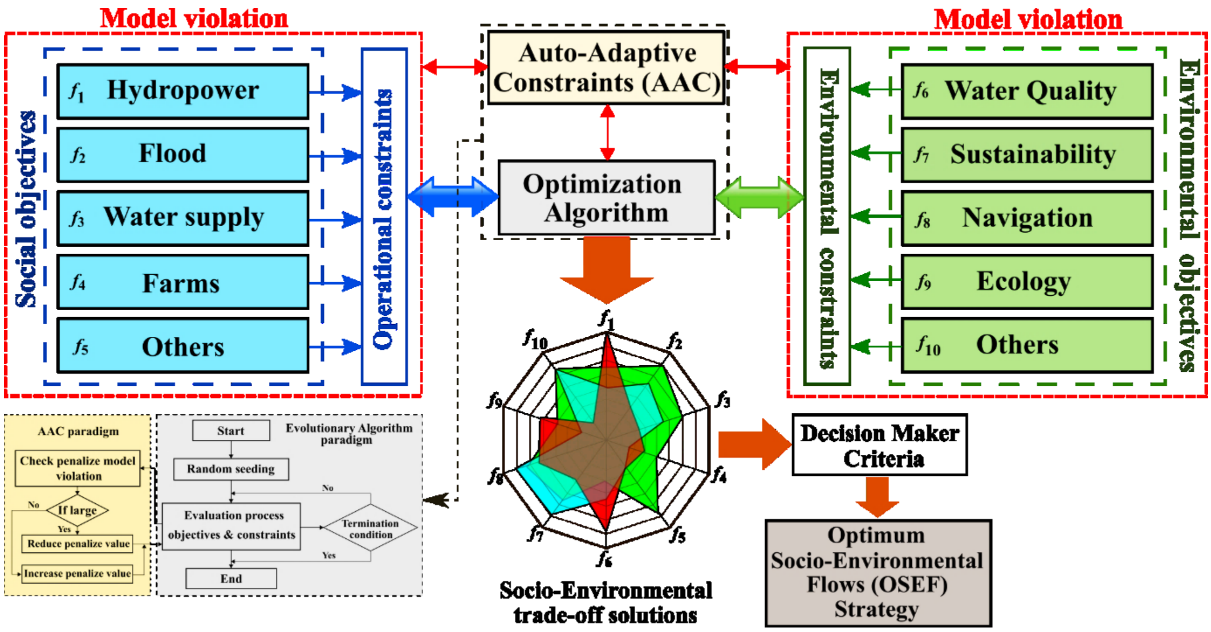

Figure 1 schematic diagram of the developed OSEF-AAC diagram in the current research. OSEF refer to Optimum Socio-Environmental Flows, and AAC to Auto-Adapted Constraints approaches.

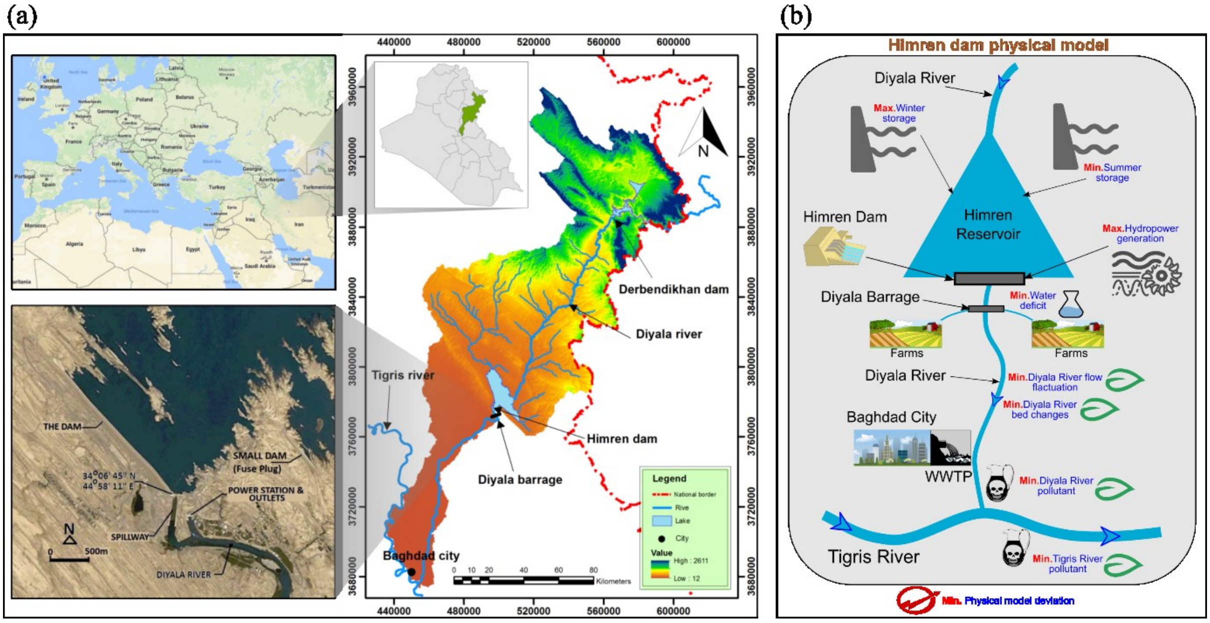

Figure 2 The location (a) and the physical model (b) of Diyala river basin and Himren dam in Iraq

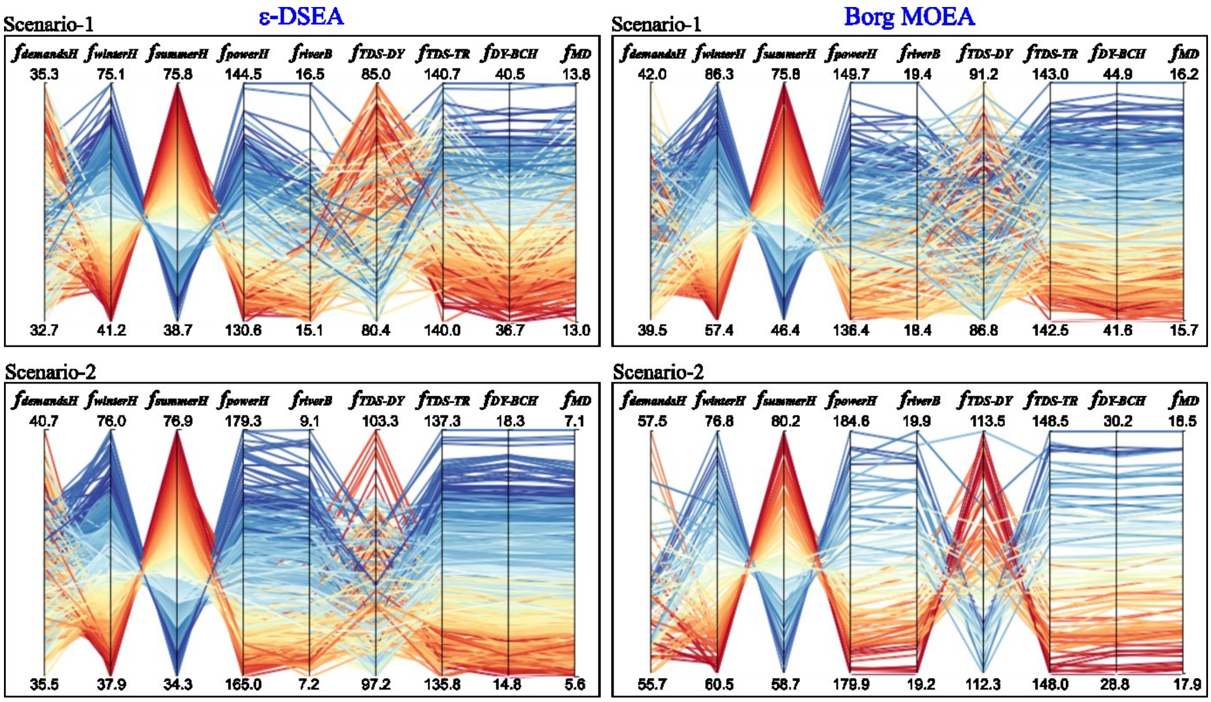

Figure 3 Pareto-front (trade-off) for the nine objective functions using Borg MOEA and ε-DSEA algorithms for Himren dam future management strategy scenarios.

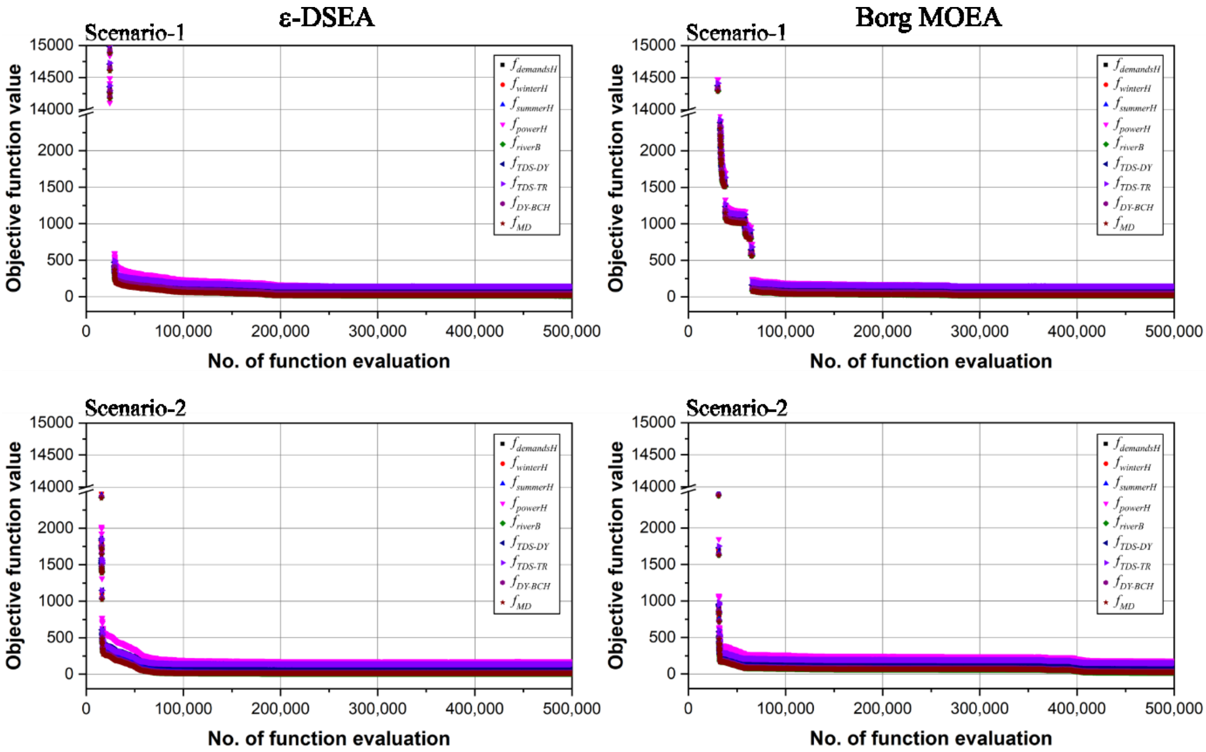

Figure 4 Illustrates objectives convergence speed over evaluation process for Borg MOEA and ε-DSEA with two inflows scenarios

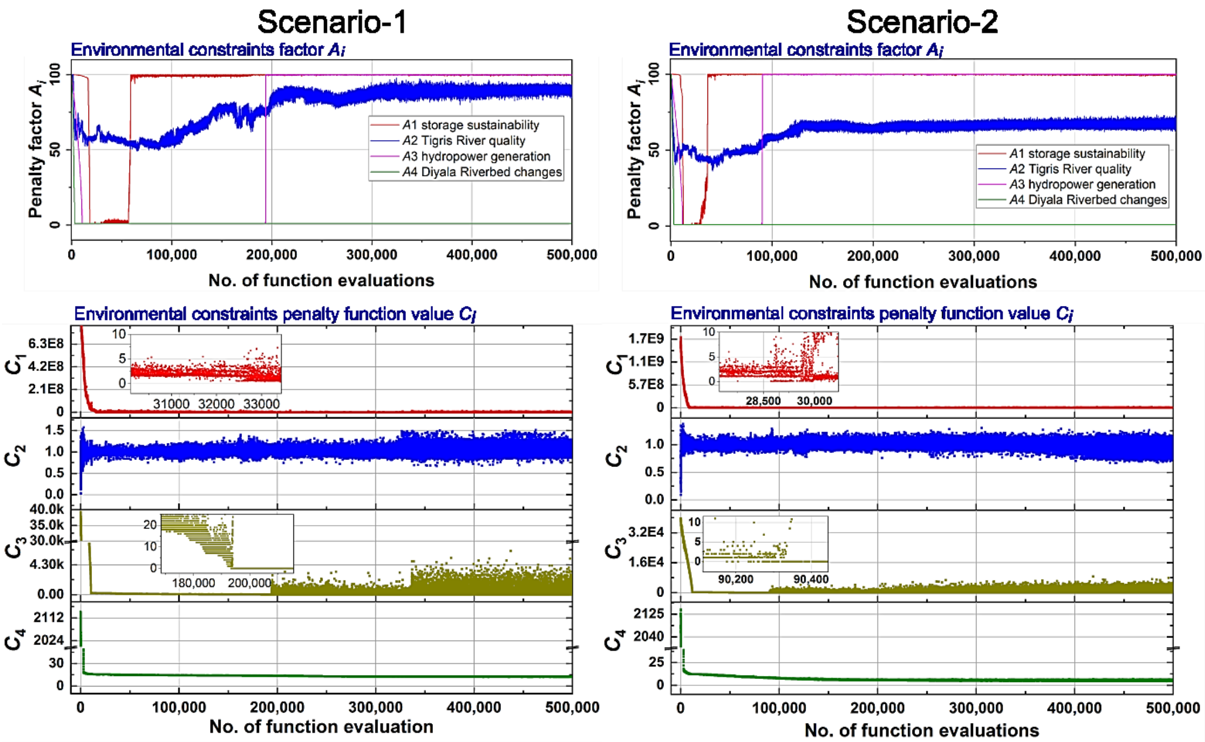

Figure 5 AAC approach for environmental constraints factors (A_i) and their corresponding penalty function values (C_i) over the evaluation process for the secondary priorities objectives for Himren dam operation policy. The magnified graphs show the region when $C_i = 0$.

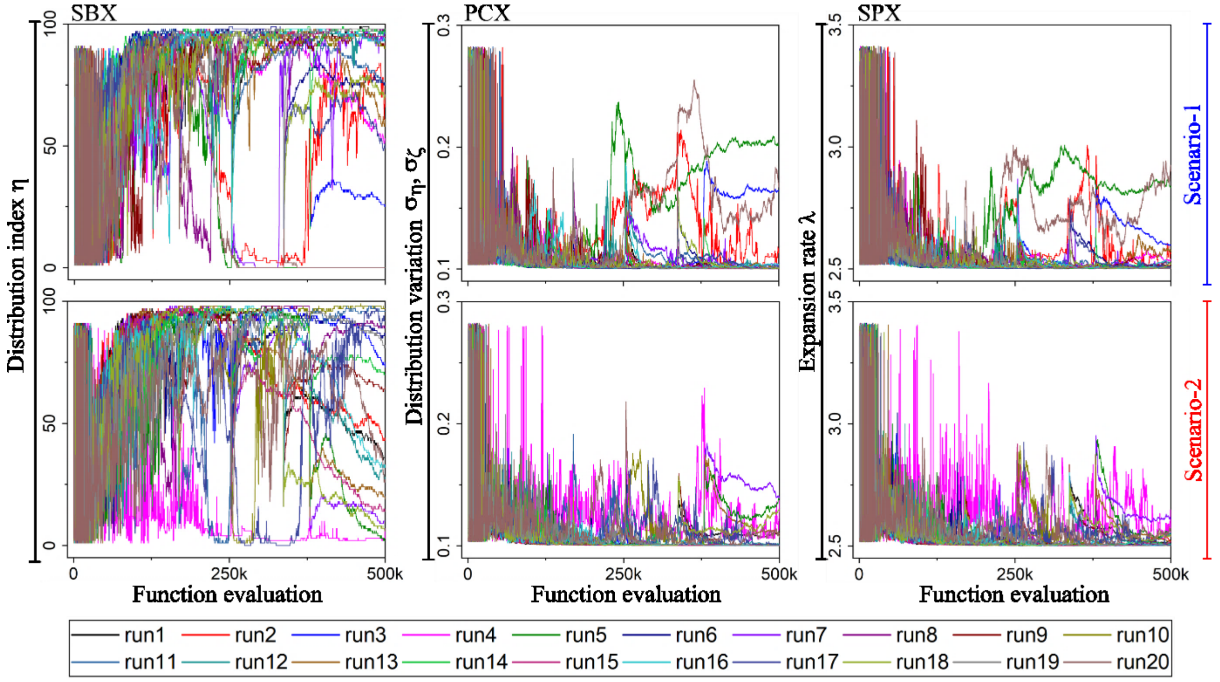

Figure 6 Sensitivity of operators' parameters during problem evaluation of 20 iterations per scenario using ε-DSEA

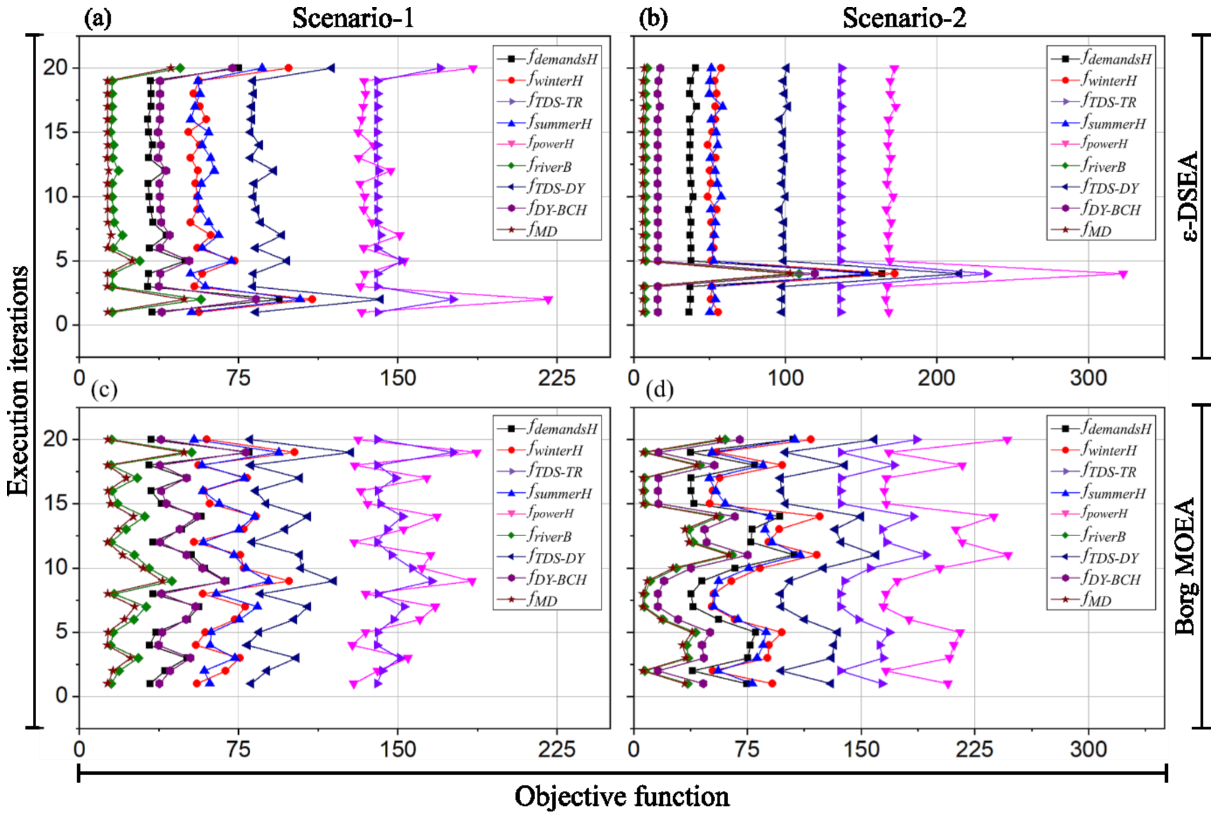

Figure 7 Algorithms' reliability over 20 iterations based on the objective functions' median. (a) and (c), are ε-DSEA and Borg MOEA's achievement for scenario-1, (b) and (d) are for scenario-2, respectively.

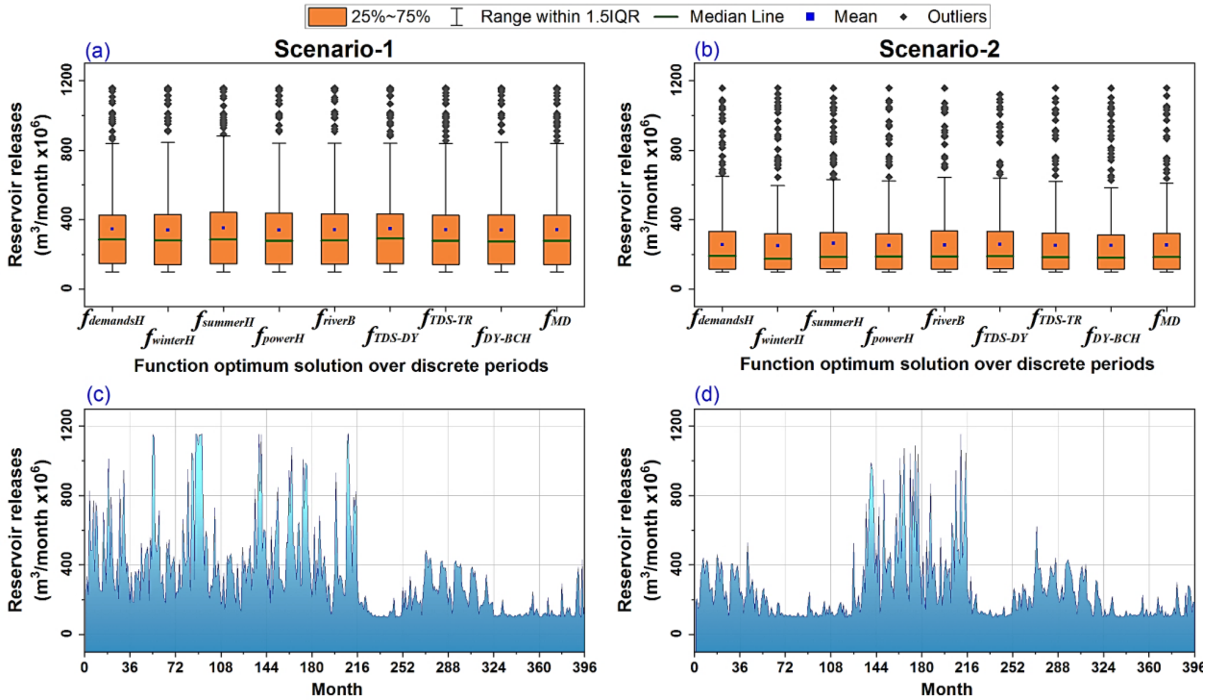

Figure 8 Optimum individual and average reservoir releases achieved by optimization model for the two scenarios. Where (a) and (b) are the releases achieved by each objective function optimum solution for scenario 1 and 2, respectively, while (c) and (d) represent the average releases for the nine objective functions optimum solutions.

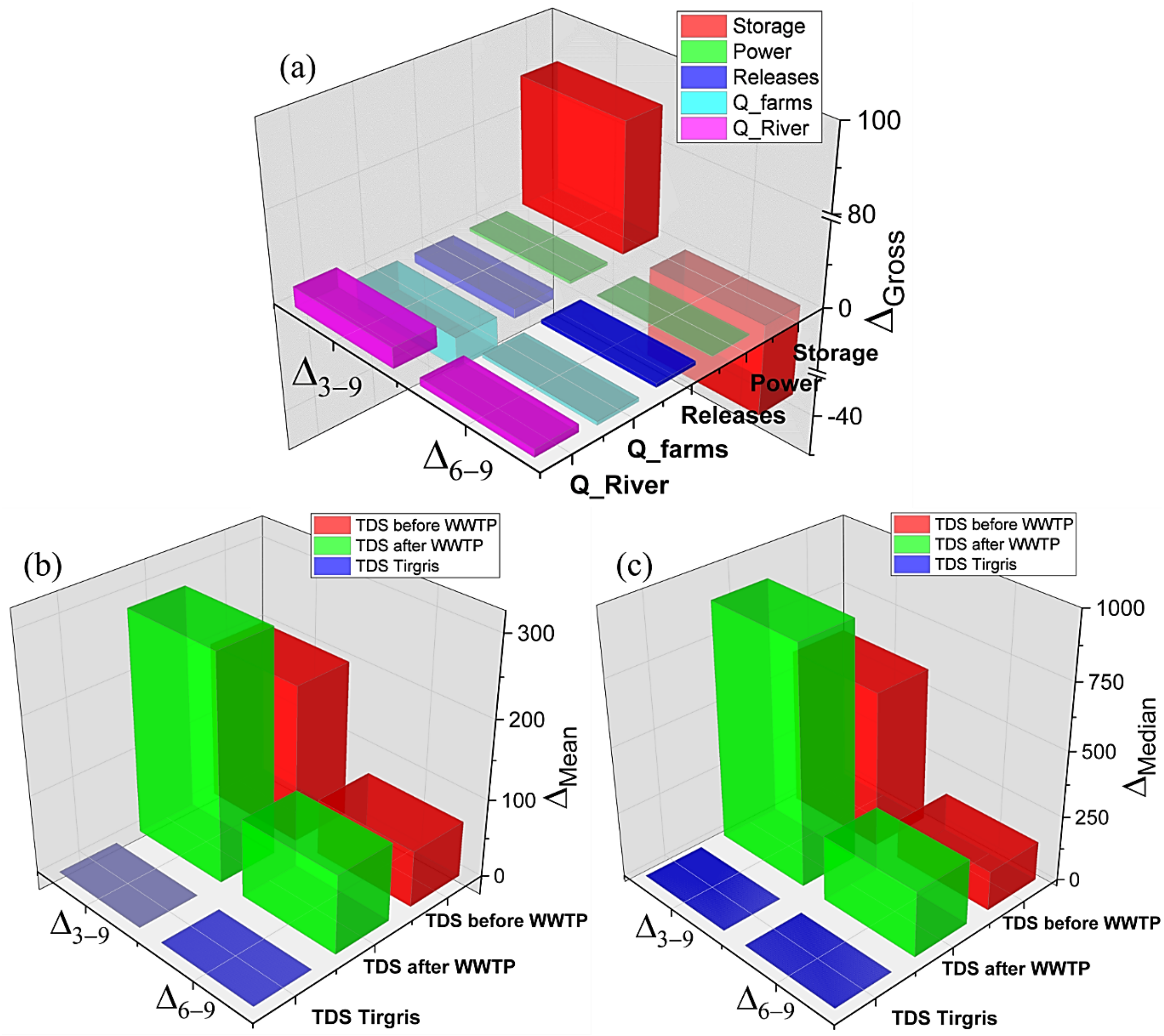

Figure 9 Illustrates the effectiveness of OSEF-AAC approach management model (M1) in comparison with M2 and M3 models. (a) is the total gross contrast of M2-M1 (Δ_{3-9}) and M3-M1 (Δ_{6-9}) of storage (BCM), power (GW), releases (BCM), farms' water delivery (Q_farms) (BCM), and river discharge (Q_River) (BCM). (b) and (c) are the TDS mean and median values (mg/l) contrast (Δ_{Mean}, Δ_{Median}) of the relevant cases (Δ_{3-9}, Δ_{6-9}) at Diyala River before and after the WWTP, and at Tigris River after the confluence, respectively. BCM = 1×10^9

TABLES

Table 1 Summary of literatures used evolutionary algorithms to optimize multi-objective reservoir operation strategy

Author	Method	Objective No.	Subject	No. of dams
Kim et al., (2008)	NSGA-II	2	Water shortage index + hydropower	1
Chang and Chang, (2009)	NSGA-II	2	Water shortage index for two dams	2
Dittmann et al., (2009)	MOES	5	Inundation + overtopping for three dams + releases	3
Reddy and Kumar, (2009)	MOPSO	2	hydropower + irrigation	1
Regulwar, (2009)	MOGA	2	hydropower + irrigation	5
Hakimi-Asiabar et al., (2010)	SLGA	3	hydropower + water supply + water quality	3
Wang et al., (2011)	MIGA	2	long term operation for water demand and storage	1
Malekmohammadi et al., (2011)	NSGA-II	2	Flood + water demands	2
Schardong et al., (2013)	MODE	3	Water demands + water quality + pumping cost	5
Kasprzyk et al., (2013)	ε-NSGA-II	6	Two cost + Three reliability + Market use	1
Giacomoni et al., (2013), Giuliani et al., (2014a)	Fitted Q-iteration	5	Two Recreation + sedimentation + water deficit + Temperature differences	1
Giuliani et al., (2014b), Giuliani et al., (2016), Zatarain Salazar et al., (2016) Zatarain Salazar et al., (2017)	Borg MOEA	6	Three water supply + hydropower + recreation + environment	1
Ahmadianfar et al., (2015)	MOEA/D	2	Flow demands + agriculture demands	3
Li and Qiu, (2015)	NSGA-II	2	Hydropower + firm power	1
Crookston and Tullis, (2016)	NSGA-II	2	Water quality + water temperature	1
Hurford et al., (2014)	ε-NSGA-II	10	Four agriculture water deficit + water losses + Hydropower + Land availability + Two Flow alteration	3
Qi et al., (2016)	MOEA/D	2	Water level + releases	1
Chen et al., (2016)	NSGA-II	5	Water supply + hydropower + flow alternation in two rivers + water quality	1
Dai et al., (2017)	NSGA-II	2	Hydropower + water alternation	2
Alrajoula et al., (2016)	PSO	1	Water allocation cost	1

Uen et al., (2018)	NSGA-II	2	Hydropower + storage	1
Li et al., (2017)	GP	2	Hydropower + water resources fee	1

Table 2 Reservoir system operation parameters and barriers (SGI et al. 2014; Alsaffar, 2017)

Parameter	Value	Unit	Parameter	Value	Unit
S_{min}^{H}	20×10^{6}	m^3	Q_{max}^{r}	1000	m^3/s
S_{max}^{H}	2400×10^{6}	m^3	TDS_{t}^{r1} at Q_{min}^{r}	2220[1]	mg/l
S_{minp}^{H}	102×10^{6}	m^3	TDS_{t}^{PS}	5000[1]	mg/l
R_{min}^{H}	20	m^3/s	TDS^{U}	500[3]	mg/l
R_{max}^{H}	447	m^3/s	Q_{t}^{PS}	15[1]	m^3/s
Pw_{min}^{H}	50	MW	γ_{m}	1486[2]	kg/m^3
Pw_{max}^{H}	7.5	MW	W_{i} (mean)	80.0	m
η_{e}^{H}	88	%	ΔBL_{max}	2.0	m
γ_{w}	≈1000	KN/m^3	d_{s}	20.0 - 0.177	mm
Q_{min}^{tuH}	38	m^3/s	NS	41	-
Q_{max}^{tuH}	98.5	m^3/s	T_W	October – March	Month
$H_{t,min}^{nH}$	15.9	m	T_S	April - September	Month
$H_{t,max}^{nH}$	30.8	m	ΔT_{t}	1	Month
Q_{min}^{r}	10	m^3/s	S_{T+1}^{H}	$0.9\times S_{t=0}^{H}$	

[1] Kubba et al. (2014), [2] Nicklow and Mays (2001), [3] Saleh (2013)

Table 3 Summary of optimum parameters achieved for Himren dam system using ε-DSEA for both scenarios

System parameter	Scenario-1		Scenario-2	
	Min.	**Max.**	**Min.**	**Max.**
Reservoir releases (MCM[1])	98.51	1158.62	98.52	1158.62
Reservoir storage (MCM)	101.55	2398.48	92.78	2399.97
Reservoir water level (m.a.s.l)	89.20	105.36	89.00	105.37
Reservoir Surface area (Km^2)	38.77	321.74	37.42	321.89
Hydropower generation (MW)	7.50	50.00	7.50	50.00
Diyala river discharge (MCM)	30.85	1108.84	30.85	1084.10
Absolute Diyala bed river changes (m)	0.00	4.62	0.00	3.00
Diyala river TDS[2] before WWTP[3] (mg/l)	540.21	2220.00	541.12	2220.00
Diyala river TDS after WWTP (mg/l)	599.73	3590.60	601.98	3590.58
Tigris river TDS (mg/l)	520.38	613.84	528.89	613.79

[1] *MCM=Million cubic meters/month;* [2] *TDS=Total dissolved solids;* [3] *WWTP=Wastewater treatment plant*

Table 4 Summary results for the reservoir system parameters achieved using average optimum reservoir releases for the two adopted scenarios.

Parameter	**Min.**	**Max.**	**Mean**	**Median**	**Std.**
Dam system			**Scenario-1**		
Releases (MCM)[1]	98.965	1158.472	343.457	280.047	249.597
Storage (MCM)	326.852	2276.070	1332.747	1348.664	394.690
Surface area (km^2)	72.581	309.496	204.078	207.795	47.784
Water level (m.a.s.l)	93.078	104.662	100.004	100.237	2.129
Hydropower (MW)	7.851	50.000	26.028	23.951	13.664
Downstream river system					
River discharge (MCM)	30.868	1105.947	186.725	102.428	216.527
TDS[2] before WWTP[3] (mg/l)	540.312	2220.000	1243.358	1071.613	564.607
TDS after WWTP (mg/l)	599.989	3589.428	1885.295	1705.264	912.914
Initial riverbed level (m.a.s.l)	25.162	60.9	35.919	31.1	9.54774
Final riverbed level (m.a.s.l)	25.256	55.641	35.248	30.954	8.332
TDS in Tigris River (mg/l)	520.395	612.886	565.871	563.159	21.314
Original farms water demands (MCM)	30.460	313.340	191.004	200.125	87.447
Achieved farms water delivery (MCM)	30.460	313.340	156.732	138.560	88.076
Dam system			**Scenario-2**		
Releases (MCM)	98.696	1153.726	254.214	186.588	195.466
Storage (MCM)	365.966	2327.516	1354.358	1371.038	431.256
Surface area (km^2)	78.292	314.673	206.327	210.459	51.884
Water level (m.a.s.l)	93.555	104.949	100.094	100.349	2.307
Hydropower (MW)	7.815	50.000	20.633	16.476	12.441

Downstream river system

River discharge (MCM)	30.855	1012.034	116.958	55.941	158.053
TDS before WWTP (mg/l)	544.052	2220.000	1474.887	1528.181	550.771
TDS after WWTP (mg/l)	609.132	3585.628	2263.959	2420.518	868.079
Initial riverbed level (m.a.s.l)	25.162	60.9	35.919	31.1	9.54774
Final riverbed level (m.a.s.l)	25.254	57.252	35.361	31.421	8.460
TDS in Tigris River (mg/l)	529.308	612.993	573.272	575.445	20.302
Original farms water demands (MCM)	30.460	313.340	191.004	200.125	87.447
Achieved farms water delivery (MCM)	30.460	313.340	137.256	130.012	81.296

[1] *is refer to million cubic meters per month;* [2] *is refer to Total Dissolved Solids;* [3] *is refer to wastewater treatment plant*

OPTIMUM SOCIO-ENVIRONMENTAL FLOWS APPROACH FOR RESERVOIR OPERATION STRATEGY USING MANY-OBJECTIVES EVOLUTIONARY OPTIMIZATION ALGORITHM

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Supplementary Data

1. Reservoir Description

The Himren dam system features in the Diyala river basin in Iraq were presented in the following paragraphs. Table A1 present the characteristics of the dam structure and its physical boundary limitations. While Table A2 illustrate average monthly meteorological data, precipitation, evaporation, river losses, and irrigation projects demands for the dam system

Table A1 characteristics of Himren dam system

Item	Value	Unit
Height	40	m
Length at crest	3360	m
Crest width at elevation 109.5 m.a.s.l	8	m
Normal operation elevation	104	m.a.s.l
Reservoir storage capacity at normal operation	2.4×10^9	m^3
Area of reservoir at normal operation	340	Km^2
Minimum dead storage level	84.1	m.a.s.l
Reservoir dead storage capacity	20×10^6	m^3
Max flood elevation	107.5	m.a.s.l
Reservoir flood storage capacity	3.56×10^9	m^3
Area of reservoir at flood elevation	450	Km^2
Minimum hydropower level	89	m.a.s.l

The spillway structure consists of five gates, each 10.6×12.5m with a maximum capacity discharge for each gate is 1360 m^3/s at flood elevation 107.5 m.a.s.l.

There are two main flow tunnels in the dam, each 6.6 m in diameter. Each tunnel divides into three smaller tunnels, one is 5.0 m in diameter which connects to the hydroelectric power station and the other two tunnels are of diameter 3.0 m and connect to the irrigation outlet. There are two generator units in the hydroelectric power station with capacity of 25 MW for each.

The Diyala Barrage is a flow control dam located on the Diyala River 90 km northeast of Baghdad city and about 10 km downstream of the Himren dam. The main purpose of the barrage is to divert the outflow on the Diyala River to the Khalis and Sadr Al-Mushtarak canals for irrigation. The length of the barrage is about 400 m and it has 23 gates, each 12m×2m. The design discharge is 1200 m^3/s, while the operation discharge is 25 m^3/s.

Table A2 Average monthly meteorological data and water demands in the dam region (SGI et al. 2014)

	T_{min} (C°)	T_{max} (C°)	T_{mean} (C°)	P^1 (mm)	E^2 (mm)	River losses[3] (%)	ID[4] ($m^3 \times 10^6$)
October	18	34	27	13	166	10	193.54
November	11	24	18	42	86	5	130.45
December	6	18	12	48	51	0	30.46
January	5	16	10	56	49	0	49.39
February	6	18	12	45	70	5	138.56
March	10	22	16	50	123	20	232.00
April	15	29	23	29	185	30	297.82
May	21	37	30	5	272	35	206.71
June	25	42	35	0	328	50	276.76
July	27	45	37	0	363	50	313.34
August	27	45	36	0	336	35	250.33
September	22	40	33	0	238	20	172.69

[1] precipitation , [2] Evaporation from reservoir lake, [3] the losses between upstream and downstream of the river in the investigated area, [4] Irrigation water demands

2. Identification of River Basin Challenges and Current Management Strategy

According to the IPCC (IPCC, 2007) Iraq has an arid environment with less than 150mm annual rainfall. Iraq has two main rivers, Tigris and Euphrates, which originate from Turkey and Iran in the north and flow south east to the Arab Gulf. Hence, its sustainability depends mainly on upstream water resources. Originating in Iran, the Diyala River is one of the main tributaries of the Tigris River. It is over 445 km long, draining an area about 32,600 km^2, of which 46% is inside Iraq and 54% in Iran (Soyuzgiprovodkhoz, 1982).The current challenges include:

1- Climate changes impact: the mean temperature may increase approximately 3 degrees and the annual rainfall may deplete by 21% for the next half-century (Abbas et al., 2016; Lelieveld et al., 2016)
2- Political impact: Iran built four dams on the river's source streams and a big water conveyance tunnel under construction were observed by Abdulrahman, (2017); Al-Faraj and Scholz, (2014) which divert water from catchment area.
3- Pollutant impact: the impact of Al-Rustamiya wastewater treatment plant discharges (470,000 m3/day, with 5000 mg/l of TDS) to the Diyala river, observed by many studies (Kubba et al., 2014; Aenab and Singh, 2014; Evan et al., 2012; WCC, 2006; CEB, 2011). This plant is located just before river confluence with the Tigris River, in the south of Baghdad city which has large density of population approaching seven million peoples and this is one of the primary treatment works for the city.
4- Leeching drains impact: two leeching drains from agriculture projects are discharging to the Diyala river, which increases the deterioration of the river environment (Soyuzgiprovodkhoz, 1982; SGI et al., 2014).

5- Water allocation losses impact: the use and impacts of traditional irrigation techniques by large agriculture projects in the downstream basin were observed by SGI et al., (2014), Al-Ansari, (2013), and Al-Ansari et al., (2014).
6- Future development plan impact: additional quantities of water will be needed for a number of planned but undeveloped agriculture projects the government intended for future investment in the basin (SGI et al., 2014).

Currently the releases from the dam system are drained through power penstocks to generate electric power. In flood events, all dam outlets including power, spillway and bottom outlets would be opened to drain excess water to avoid hazard damages to the dam structure. However, in the arid environments, the flashing flood wave usually last a matter of hours or a maximum few days and its effects dissipated when considering average monthly inflows dataset. Hence, any spillway operation was not considered in this study's model. The Diyala Barrage's current operational policy focuses on delivering water to the irrigation projects rather than enhancing river environment, and is included.

In water resources decision making the scarcity condition of domestic demands is a priority, while other requirements like agriculture and hydropower generating will often be reduced or masked. Hence, this aspect of river basin management needs more attention from the decision makers (the Government of Iraq) to improve its environmental and economic benefits by employing innovate strategies.

3. Area-Storage and Head-Storage Relationships for Himren Dam

Polynomial equations (Equation A4 and A5) for the area-storage and head-storage relation were constructed depending on the design data available in the NCWRM. The evaporation losses from the reservoir surface area at time *t* (Ar_t) in meter square, which can be expressed as follows, where the storage (S_t) in million cubic meters (MCM):

$$Ar_t = 2.3 \times 10^7 + 156915.48 \times S_t - 16.369 \times S_t^2 + 0.0012 \times S_t^3 \quad \text{(A1)}$$

Equation A2 is used to calculate the water head in the reservoir for hydropower generation, where (H_t^H) is Himren water level in meters (m) and (S_t) is reservoir storage in MCM:

$$H_t^H = 86.51 + 0.031 \times S_t - 4.37\times10^{-5} \times S_t^2 + 4.33\times10^{-8} \times S_t^3 - 2.55\times10^{-11} \times S_t^4 + 8.63\times10^{-15} \times S_t^5 - 1.54\times10^{-18} \times S_t^6 + 1.13\times10^{-22} \times S_t^7 \quad \text{(A2)}$$

5. Promotion of Diyala Barrage Operation Policy

In order to enhance the river environment, a new operating policy was proposed for Diyala barrage. It provides priority to the river rather than irrigation projects. When the reservoir releases (R_t) is less than the half of the total demands ($R_t < 0.5 \times DD_t$), which include the irrigation demands (ID_t) and water supply demands (Q_{min}^r), the releases from the barrage will be

$$Q_t^r = Q_{min}^r + (5\% \times R_t) \quad \text{(A3)}$$

For example, if the release from the reservoir is 100 m^3/sec, and the total demands was 250 m^3/sec, then the river discharge will equal to 10+(0.05×100) = 15 m^3/sec, and the remaining discharge (85 m^3/sec) will delivered to the irrigation projects. In this case when the reservoir releases are between the half and total demands ($0.5 \times DD_t \le R_t \le DD_t$), the river discharge will be as follows, and the remaining will delivered to the irrigation projects

$$Q_t^r = Q_{min}^r + (10\% \times R_t) \quad \text{(A4)}$$

Otherwise ($R_t > DD_t$), the river discharge will be

$$Q_t^r = \begin{cases} R_t - ID_t & if\ R_t - ID_t > Q_{min}^r + (10\% \times R_t) \\ Q_{min}^r + (10\% \times R_t) & otherwise \end{cases} \tag{A5}$$

6. Reservoir System Predicted Future Resources

A historical thirty-three year dataset from 1981 to 2013 provided by the Iraqi Ministry of Water Resources/National Centre for Water Resources Management (NCWRM) (Alsaffar, 2017a) was used to model reservoir inflows. These data were smoothed using Fast Fourier Transformation (FFT) to reduce any potential errors observed by NCWRM (Alsaffar, 2017a) such as reservoir seepage losses, unauthorized direct pumping from reservoir lake, recharges from neighbouring farms located on reservoir boundaries, etc., and smoothing out any flooding waves which directly affects the average monthly records. Figure A2a illustrates four smoothing options in which the 6 points cycle smoothing showing consistent behaviour with the original data, hence it is adopted for the model. The same smoothing option was also adopted for the Tigris river historical discharge (Alsaffar, 2017a).

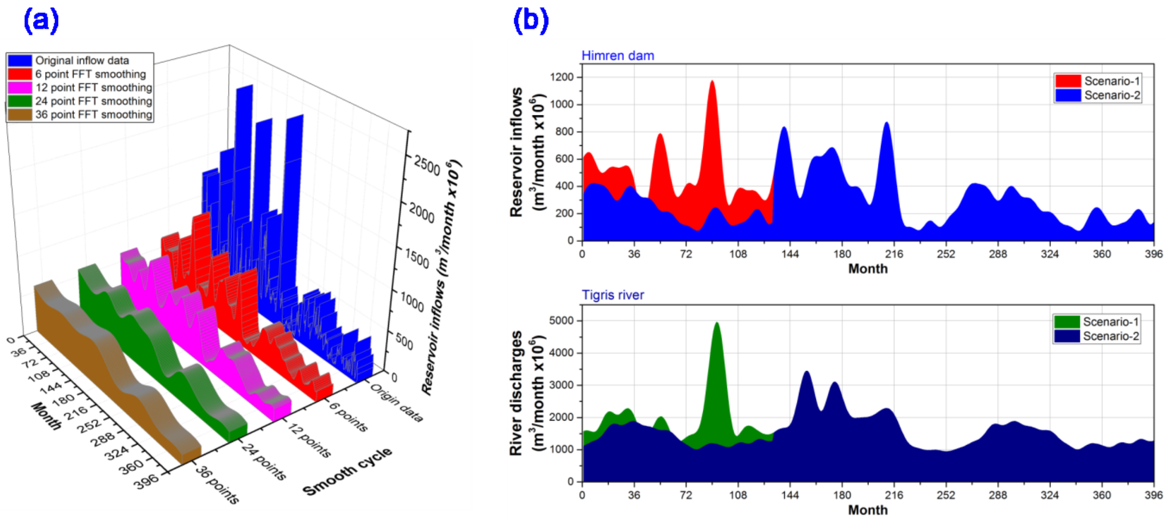

Figure A2 Himren reservoir inflows smoothing and scenarios, where (a) shows the smoothing options using Fast Fourier Transformation (FFT) for thirty-three years (1981-2013), and (b) shows the model scenarios for Himren dam and Tigris river for future projection for thirty-three years

Figure A2a also illustrates two hydrological periods, wet and dry. The wet period is from 1981 to 2000, and the dry is from 2000 to 2013 (from 0 to 240 and from 241 to 396 in Figure 4a, respectively). Hence the first scenario (scenario-1) is the projection of these cycles for the next thirty-three years to investigate the model performance and reliability. A second scenario (scenario-2) was adopted to adapt with possible future climate changes in the region (Abbas et al., 2016) by swapping the first eleven wet years by dry years. The same methodology was adopted for the Tigris river discharge. Figure A2b shows the two proposed model scenarios (Alsaffar, 2017; Zhang et al., 2017).

8. Optimization Parameters and Comparative Results

Table A3 illustrates the algorithm parameters used to solve the many-objective problem. The ε-DSEA algorithm has an auto-adapt parameter mechanism, through which the operators parameters tuned dynamically to adapt with performance of the operator that generates dominance solutions. Hence, the operators' parameter is tuned over the evaluation process. More details about Borg MOEA and ε-DSEA algorithms could be found in (Hadka and Reed, 2013) and (Al-Jawad and Tanyimboh, 2018), respectively.

Table A3 Parameter values used in the optimisation algorithms

Parameters	Borg	ε-DSEA[a]	Parameters	Borg	ε-DSEA
Initial population size	100	100	SPX parents	10	3
Tournament selection size	2	2	SPX offspring	2	2
SBX crossover rate	1.0	1.0	SPX expansion rate λ	3	[2.5, 3.5]
SBX distribution index η	15.0	[0, 100]	UNDX parents	10	10
DE crossover rate CR	0.1	[0.1, 1.0]	UNDX offspring	2	2
DE step size F	0.5	[0.5, 1.0]	UNDX σ_ζ	0.5	[0.4, 0.6]
PCX parents	10	10	UNDX σ_η	$0.35/\sqrt{L}$	$[0.1, 0.35]/\sqrt{L}$
PCX offspring	2	2	UM mutation rate	$1/L$	$1/L$
PCX σ_η	0.1	[0.1, 0.3]	PM mutation rate	$1/L$	$1/L$
PCX σ_ζ	0.1	[0.1, 0.3]	PM distribution index η_m	20	20

L is the number of decision variables. The permissible range for dynamic parameters is shown in brackets. The parameters σ_η and σ_ζ are defined in Section 2.1.5. [a]The initial values of dynamic parameters used in ε-DSEA are as shown for Borg MOEA.

Table A4 illustrates the summary of the results for 20 random seeding optimization runs for both algorithms and for both scenarios. It can be seen that the ε-DSEA is outperform Borg MOEA in almost all results for scenario-1 and scenario-2. Hence, its results were adopted for the river basin management.

Table A4 Results summary for scenario-1 and scenario-2 for 20 optimization runs. The best achievements are shaded with grey

	Scenario-1							
	Borg MOEA				ε-DSEA			
	Best	Mean	Median	Std	Best	Mean	Median	Std
$minf_{demandsH}$	31.483	45.532	43.555	13.723	30.799	38.779	32.446	16.362
$maxf_{demandsH}$	35.028	48.205	46.198	13.131	33.305	41.740	35.382	16.137
$minf_{winterH}$	39.237	59.837	62.126	16.956	38.996	48.065	41.455	16.783
$maxf_{winterH}$	74.582	87.206	85.561	9.811	71.422	82.576	77.842	13.989
$minf_{summerH}$	37.779	55.811	55.415	15.181	31.467	44.755	39.302	15.138
$maxf_{summerH}$	75.787	87.217	85.098	8.184	74.230	83.614	81.602	10.389
$minf_{powerH}$	125.131	146.963	143.848	20.257	127.656	139.384	130.290	22.529
$maxf_{powerH}$	138.206	157.092	154.250	17.092	140.850	153.159	144.683	21.148
$minf_{riverB}$	14.433	23.786	20.156	10.558	14.424	19.873	15.221	11.432
$maxf_{riverB}$	15.881	24.850	21.375	10.329	15.863	21.299	16.784	11.539
$minf_{TDS\text{-}DY}$	77.339	94.193	91.999	14.506	78.840	87.517	80.841	15.654
$maxf_{TDS\text{-}DY}$	82.034	97.840	94.596	13.457	82.740	92.507	86.808	14.829
$minf_{TDS\text{-}TR}$	139.827	147.364	143.712	9.722	139.781	143.919	140.024	10.095
$maxf_{TDS\text{-}TR}$	140.668	148.008	144.583	9.629	140.561	144.808	140.858	10.308
$minf_{DY\text{-}BCH}$	35.883	46.806	44.042	11.497	35.730	41.640	36.756	12.502
$maxf_{DY\text{-}BCH}$	40.058	49.948	47.518	10.861	39.419	45.493	40.782	12.314
$minf_{MD}$	12.823	20.521	16.934	9.806	12.747	16.970	13.019	10.239
$maxf_{MD}$	13.812	21.245	17.889	9.696	13.608	17.934	13.905	10.441
	Scenario-2							
$minf_{demandsH}$	35.883	63.251	69.580	24.169	34.427	42.533	35.712	28.531
$maxf_{demandsH}$	40.202	66.526	72.369	23.345	38.557	46.855	40.594	27.836
$minf_{winterH}$	37.596	69.865	77.860	26.836	34.571	45.621	38.851	28.756
$maxf_{winterH}$	70.836	95.529	93.795	21.432	65.572	78.562	74.404	23.762
$minf_{summerH}$	32.222	60.365	65.644	22.458	31.173	40.292	33.581	25.883
$maxf_{summerH}$	68.834	89.888	91.707	15.502	68.696	78.652	73.888	19.724
$minf_{powerH}$	161.468	194.588	202.797	29.139	163.025	173.334	165.069	35.040
$maxf_{powerH}$	174.369	204.068	210.633	27.399	174.001	185.377	178.131	33.059
$minf_{riverB}$	6.517	27.512	31.036	19.765	6.481	12.217	7.034	22.822
$maxf_{riverB}$	8.226	29.155	32.747	19.549	8.036	14.062	9.002	22.731
$minf_{TDS\text{-}DY}$	94.843	120.500	126.509	22.155	94.688	103.030	97.155	26.189
$maxf_{TDS\text{-}DY}$	99.422	123.679	129.047	21.350	98.643	107.835	102.250	25.378
$minf_{TDS\text{-}TR}$	135.976	155.721	158.387	18.986	135.732	140.843	135.954	21.657
$maxf_{TDS\text{-}TR}$	137.157	157.026	159.932	18.945	136.963	142.154	137.246	21.637
$minf_{DY\text{-}BCH}$	14.929	36.614	40.731	20.245	14.500	20.254	14.885	23.309
$maxf_{DY\text{-}BCH}$	18.062	39.423	43.187	19.802	17.392	23.374	18.187	22.993
$minf_{MD}$	5.712	25.651	28.443	19.125	5.437	10.586	5.658	21.809
$maxf_{MD}$	7.028	27.049	30.030	19.046	6.763	12.006	7.054	21.773

Table A5 presents the computational summary (CPU time) of the results for both algorithms and for both scenarios used to solve the optimization problem. It is clearly that also ε-DSEA superior Borg MOEA in almost all cases.

Table A5 The summary of computational results of scenario-1 and scenario-2 for both algorithms using 20 runs. All results are in minutes and the best achievement are shaded with grey

	Scenario-1		Scenario-2	
	Borg MOEA	ε-DSEA	Borg MOEA	ε-DSEA
Min.	39.88	40.37	46.00	31.51
Max.	85.16	57.61	87.98	124.01
Mean	55.65	47.91	59.25	45.50
Median	54.15	46.62	57.05	42.45
Std.	11.24	5.70	9.75	19.76

The above results shows that ε-DSEA has better diversity and faster convergence than Borg MOEA, which refer to the stability and reliability of the algorithm to generate optimum solutions in fewer random seeding runs. Hence, ε-DSEA is computationally more economic than Borg MOEA.

9. Reservoir Optimization Model

Figure A3 and A4 illustrate the results from the average optimum reservoir releases utilization for both scenarios. It shows the impact of dry weather on the river basin model, which represented by scenario-2. On the other hand, the sensitivity of system component was observed toward any changing in the system inflows.

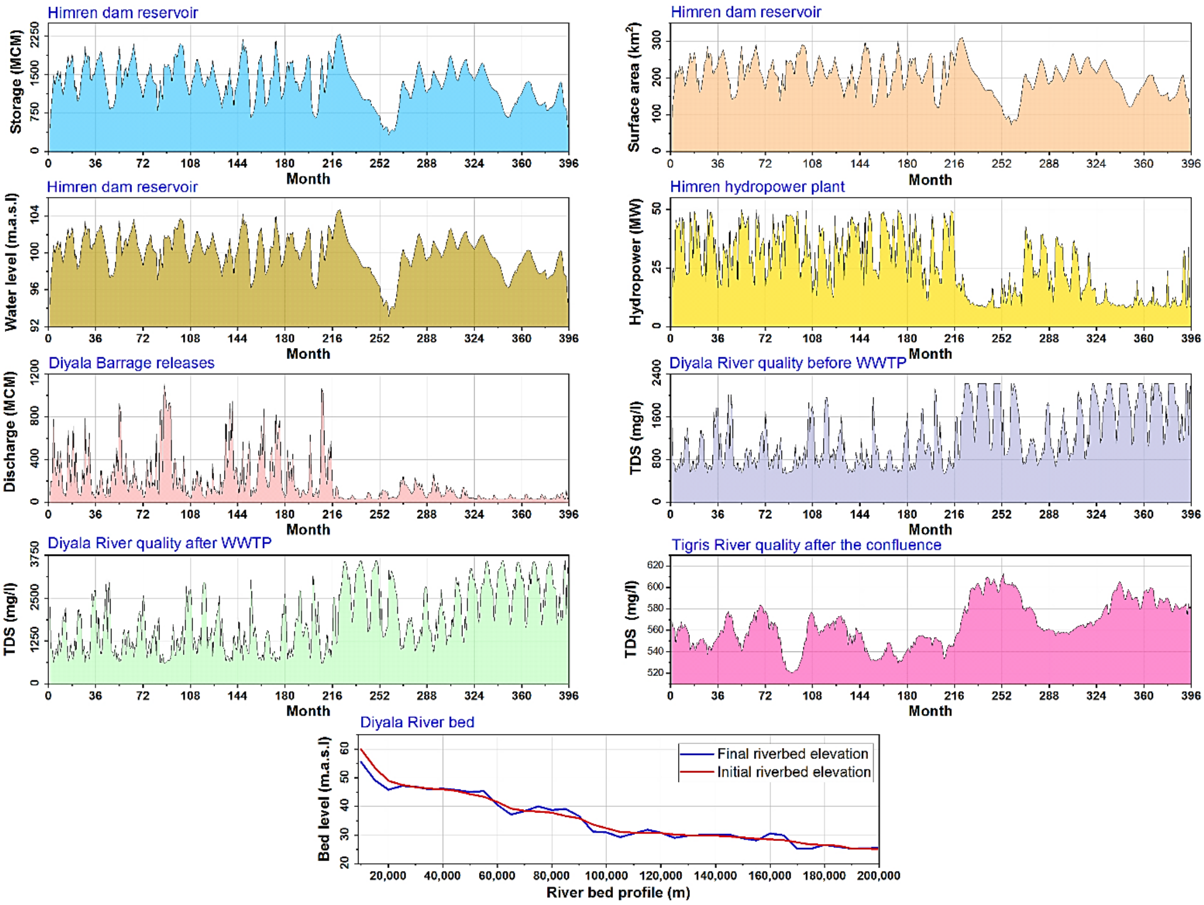

Figure A3 Reservoir system features achieved for scenario-1 using the average optimum reservoir releases.

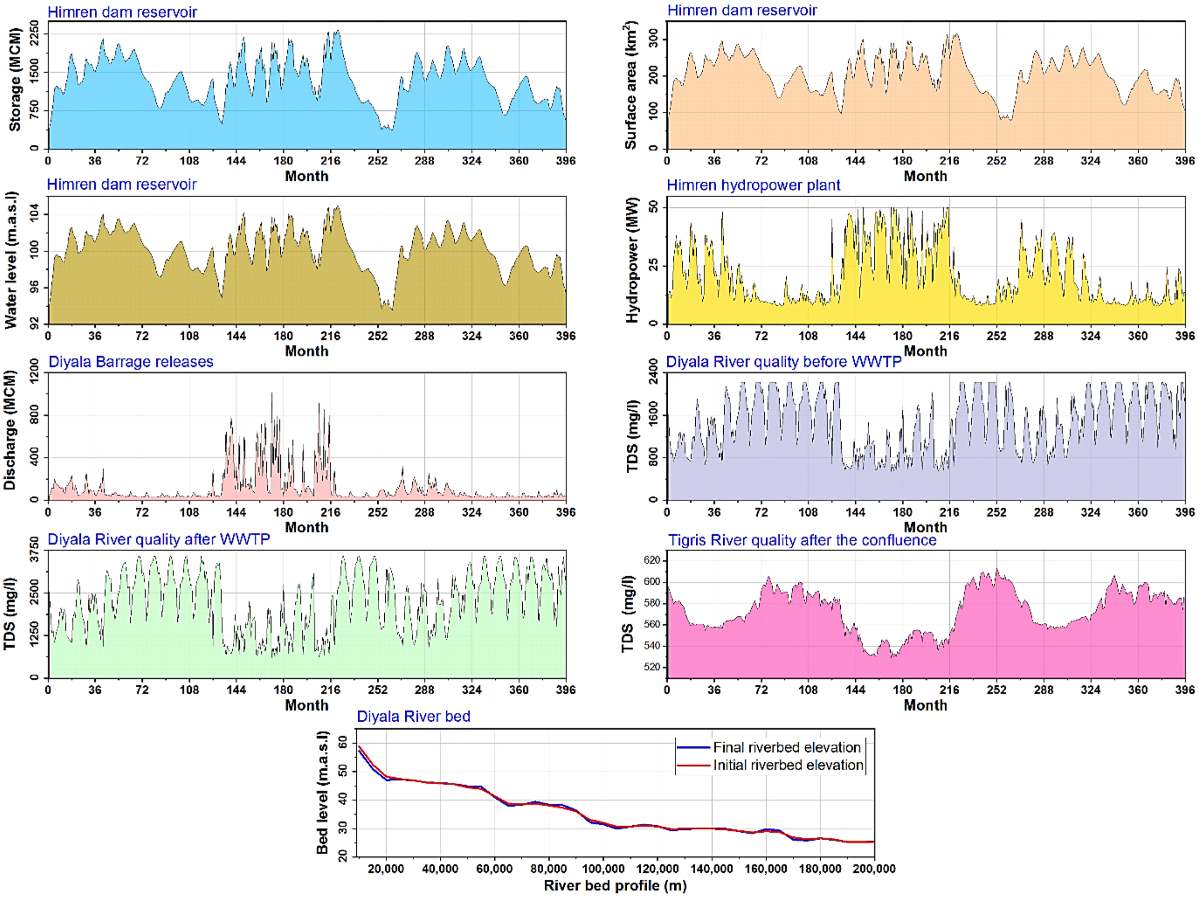

Figure A4 Reservoir system features achieved for scenario-2 using the average optimum reservoir releases.

10. Recommendations

In order to improve the lower Diyala river basin environment, the following suggested policy changes should be considered for different sectors:

- *Environmental Sectors:* A monitoring and mitigation strategies must be developed to solve the high pollutant concentration from Al-Rustumiya wastewater treatment plan outflows, which increases both pollutant level in Diyala and Tigris Rivers water and the remediation cost downstream water supply projects. Moreover, detail hydrological study and field survey are needed to explore and control sediment transport in the river.
- *Social Sector:* Adopt developed irrigation techniques (e.g. sprinkles, drips) to reduce losses due to crop water allocations, evaporation and infiltration. Also, change summer crop types or reduce crop pattern to reduce water exploitation in summer for this part of the river basin. Further, rehabilitate water conveyance infrastructure (e.g. main channels, outlets, gates, etc.) and restrict water exploitation in the middle part of the river basin (upstream region of Himren dam) to mitigate water delivery losses and to robust water resource sustainability for the lower part of the basin. Another actions are to remove any unauthorized water exploitation pumps and develop a comprehensive seepage model from the Himren reservoir to improve accuracy of the actual water budget.

Additional to above, a policy for adopting advanced daily monitoring system for data collections and flood alarm system should be consider to improve water resources management and forecasts in the basin.

However, the middle part of the basin has significant effect on the considered reservoir system, which includes a multipurpose dam and potential groundwater storage. These could be integrated with the river basin model management by using integrated water resources management principles to improve understanding of the system. Finally, an International agreement with Iran should be sought for the Diyala River and its tributaries to maintain the long-term sustainability of river water resources.